Influences of climate, landscape and vegetation proximity on the spatial distribution of the Tasmanian *Eucalyptus* leaf beetle, *Paropsisterna bimaculata* in Tasmanian *Eucalyptus* plantations

by

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Declaration

This thesis contains no material which has been accepted for the award of any other degree or diploma in any tertiary institution, and to the best of my knowledge and belief, contains no material previously published or written by another person, except where due reference is made in the text of the thesis.

Signed

Sophie Edgar BSc.

Date

Annotation

This thesis is an uncorrected text as submitted for examination.

Abstract

The distribution of the beetle Paropsisterna bimaculata was related to 33 environmental covariates distributed across in Tasmania. This beetle is an economic pest in Eucalyptus plantations, episodically occurring in large aggregations that damage tree canopies through overgrazing. A number of hypotheses relating to beetle outbreaks have been proposed by various researchers. Random forest modelling, a powerful non-parametric statistical approach that has not been frequently applied before in ecology, was used to assess specific predictions of these hypotheses. The models were developed using landscape layers and proximity to vegetation layers that were created using GIS for multiple combinations of climate variables and districts. The climate combinations assessed included: (1) mean summer maximum temperature and summer rainfall for survey years, (2) 30 year average for mean summer maximum and summer rainfall, (3) 30 year average for climate variables, (4) 30 year average for climate variables and mean summer maximum temperature and summer rainfall for survey years. The district combinations included all districts, Bass only, and all districts excluding Bass.

Locations less than 10 kilometres from Poa grasslands showed highest beetle numbers, while increasing elevation also showed a strong positive relationship with P. bimaculata populations, and mean annual summer rainfall and survey year were important in the district of Bass. Thus, in terms of prior hypotheses, Poa appears to be an important overwintering site for P. bimaculata; beetle populations increase with elevation; beetle populations increase with age of plantation between 2 and 8 years; and Bass has greater variability than other districts in beetle density. Model outputs did not support, or only weakly supported, hypotheses that suggest beetle numbers are highest at highly productive sites, and are affected by the shape and size of forestry coupes and by plantation species.

The random forests model with least error was based on all districts except Bass for thirty-year climate average data plus summer mean rainfall and summer mean maximum temperature data. A cost-benefit analysis nevertheless indicated that directing the ongoing beetle survey effort on the basis of model outputs would not reduce costs compared to the current broad-scale monitoring program. The model did,

however, generate state-level maps of value to forestry workers when assessing the likelihood of beetle outbreaks in their districts.

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Chapter 1 Introduction

1.1 Background

The Tasmanian Eucalyptus leaf beetle, *Paropsisterna bimaculata*, formerly known as *Chrysophtharta bimaculata*, is a major insect pest of commercial *Eucalyptus* forests. It regularly causes chronic defoliation of new season's growth over large areas of plantations, and management of *P. bimaculata* is of highest importance in producing economically viable timber in Tasmania. *Paropsisterna bimaculata* attacks can decrease the amount of annual growth by as much as fifty percent each year (Clarke *et al*. 1997). Elek (1997) also found that after eight years the volume of wood in a *Eucalyptus regnans* plantation was reduced by almost 30%, compared with a plantation where the beetles were excluded. Even small numbers of beetles in a plantation can result in a substantial reduction in growth over one season (Leon 1989). Thus *P. bimaculata* has a significant detrimental effect on Eucalypt plantations, causing major losses in value of harvested wood due to downgrading of timber form and longer rotation times than normal production schedules (Leon 1989).

Large numbers of defoliating insect species occur in Tasmania, with the genus *Paropsis* (Coleoptera: Chrysomelidae) having over 400 species, most of which feed on foliage of *Eucalyptus* species as larvae and adults (Clarke *et al*. 1997; Simmul *et al*. 1999)**.** Of these defoliants, the majority of damage is done by *P. bimaculata* (Greaves 1966). Adult *Paropsisterna bimaculata* beetles are dome shaped, approximately 9-10 mm in length and 7 mm in width, with colour ranging from reddish-brown (Figure 1**)**, when they first appear after overwintering, to light green during summer (Greaves 1966; De Little 1983; Leon 1989; Candy 1999). The beetles are native to Victoria and Tasmania (Elek 1997) and their main native hosts are the *Monocalyptus* species *Eucalyptus regnans*, *E. delegatensis*, *E. obliqua* and the introduced mainland *Symphyomyrtus* species *E. nitens*. (Elliott *et al*. 1992).

Figure 1: Adult *Paropsisterna bimaculata* showing different colourmorphs

In Tasmania, *E. regnans* was once widely used for plantation forests, however *E. nitens* is now the preferred species (Elek 1997). *Eucalyptus globulus* is also present in parts of the state, but requires a warmer climate than *E. nitens* (Wardlaw 2010). If the two species *E. regnans* and *E. nitens* are present, *P. bimaculata* preferentially attacks *E. regnans*, however, larval survival and growth is better on *E. nitens* with 1.5 times more foliage consumed by *P. bimaculata* survivors on *E. nitens* than on *E. regnans* (Elek 1997; Candy 1999; Baker *et al.* 2002). De Little *et al.* (2008) found no evidence of species preference between *E. nitens* and *E. globulus.* While Wardlaw *et al.* (2010) found that chrysomelid damage was significantly more common on *E. globulus* than *E. nitens*, they believed this preference for *E. globulus* to be an artifact of the difficulty in distinguishing chrysomelid damage from *Gonipterus* damage, which is a pest more commonly occurring on *E. globulus* than *E. nitens.*

Paropsisterna bimaculata rarely attack trees less than three years old (De Little *et al*. 2008), preferring trees between 1 and 7 m height. Older trees above 7 m in height are also sometimes defoliated, but to a lesser degree (Greaves 1966; De Little 1983). As *P. bimaculata* preferentially attack adult foliage, trees below 3 m in height are not commonly attacked because of the lack of adult foliage (Candy 1999). When below 3 m high, eucalypts are instead more likely to be attacked by browsing mammals (Greaves 1966).

Leaf nitrogen and leaf toughness are the dominant factors affecting larval growth, with secondary plant substances found in eucalypts (such as tannins and terpenoids) having little effect (Clarke *et al.* 1997). As new-season growth or flush foliage is soft and high in nitrogen, its availability is a dominant influence on ovipositioning and *P. bimaculata* population dynamics, rather than the particular host species (Clarke *et al.* 1997; Candy 1999). While ovipositioning usually occurs on new leaf foliage, eggs are sometimes found on foliage from the previous year (Greaves 1966).

1.2 Life cycle of P. bimaculata

Egg laying first occurs in mid-late November and continues throughout summer until mid-February (Figure 2), depending on patterns of temperature variation each year (Greaves 1966; De Little 1990; Clarke *et al*. 1997). Eggs are laid in discrete lines of 10-30 eggs on either surface of the leaf (Figure 3) (Greaves 1966; Clarke *et al.* 1997), often close to the tip of the leaf (Howlett *et al.* 2003). Although originally thought to have two generations per year (bivoltine) by Greaves (1966), more recent studies consider the beetles to have one generation per year (univoltine) since the teneral adults do not reach sexual maturity until the following spring (De Little 1983). Two or three egg laying peaks often occur during summer and autumn (Candy 1999). Eggs hatch after approximately 10 days and the neonate larvae consume their chorion prior to feeding on the flush foliage (Greaves 1966; Candy 1999).

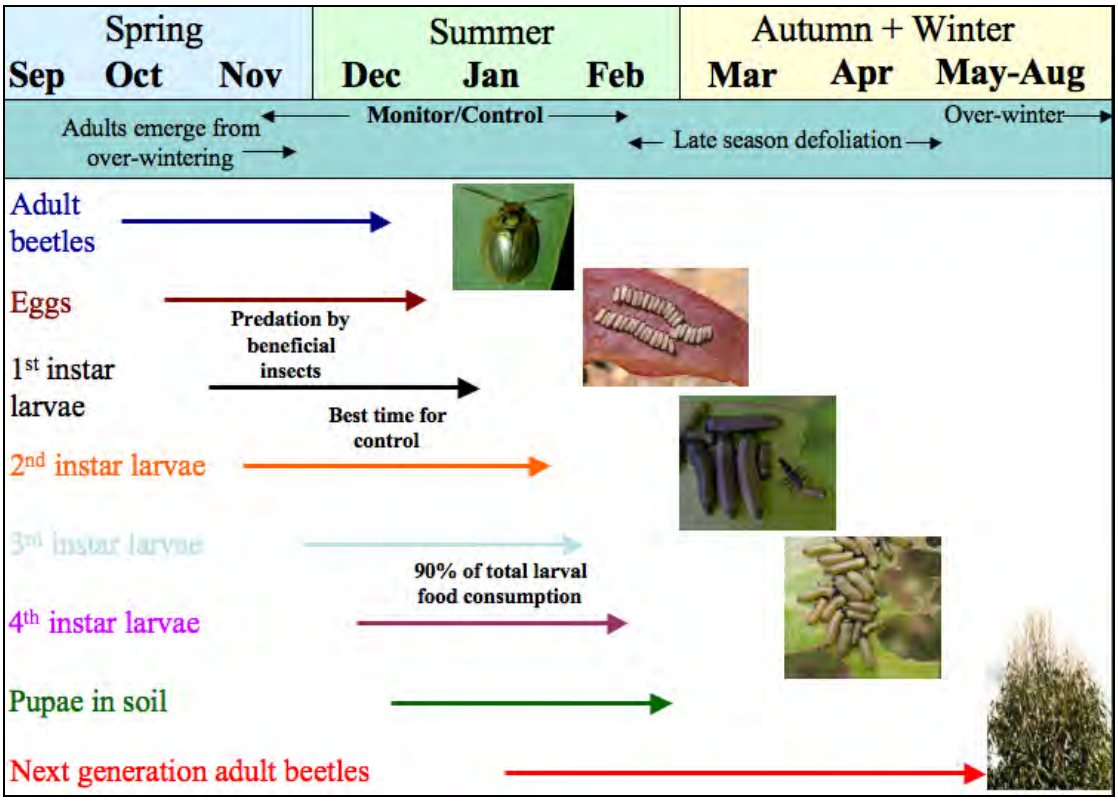


Figure 2: Lifecycle of *P. bimaculata* (Forestry Tasmania)

The grub-like larvae are dark-green to black in appearance (Figure 3**)** (Leon 1989) and gregariously feed on new season's growth (De Little 1983; Leon 1989). Damage done by larval feeding is quite distinct from adult feeding damage as seen in Figure 4 (Greaves 1966). Although both adults and larvae feed on new season's foliage (Elek 1997), adults feed singularly, chewing inwards from the edges of the leaves towards the midrib, while leaving a characteristic scalloping pattern on the leaf margins (Greaves 1966; De Little 1983; Simmul *et al.* 1999). Colonies of larvae feed on the new-growth, potentially stripping the host trees of all young leaves and shoots or leaving just the midribs and margins (De Little 1983; Leon 1989; Simmul *et al*. 1999). This can give the tops of badly affected trees a twiggy broom like appearance ("broom-topping") (Leon 1989).

Figure 3: Juvenile beetles of *P. bimaculata* showing from left to right a) rows of eggs and first instar larvae, and b) third instar larvae

Figure 4: Damage from adult *P. bimaculata* beetles (scalloping) and larvae (rougher edges to the midrib).

Over approximately 21 days to a month, the larvae develop through four instars and reach a length of 12-14 mm (Greaves 1966; Leon 1989; De Little 1990; Clarke *et al.* 1997). Although all instars feed, it is estimated that the majority of damage caused by larvae is during the third and fourth instar when about 90% of the larvae's food intake occurs (Greaves 1966; Leon 1989). Following completion of feeding, larvae become sluggish and drop to the ground to pupate in small prepupal cells in the soil (Greaves 1966). The new adult *Paropsisterna bimaculata* beetles emerge after 12-15 days before commencing feeding and then overwintering nearby (Greaves 1966; Clarke *et*

al. 1998).

Paropsisterna bimaculata are highly mobile beetles and subpopulations in central Tasmania have been found to have high numbers of immigrants, which are undistinguishable from a single interbreeding population (Clarke *et al*. 1997; Congdon *et al*. 1997). Large numbers of beetles move from one tree patch with favourable conditions to another (Clarke *et al.* 1997). This usually occurs on sunny days. During unfavourable weather, such as cool temperatures or strong winds, they seek shelter in leaf litter on the forest floor (Greaves 1966; Leon 1989). *Paropsisterna bimaculata* adults were found to be spatially aggregated up to a distance of 110 m, negatively correlated at around 250 m, and have no spatial correlations at a between-coupe scale (Clarke *et al*. 1997). As adult *P. bimaculata* beetles are highly mobile, they possibly disperse large distances to find overwintering sites, however, the abundance of beetles found overwintering within, or near the margins of, regrowth forest suggests that the beetles remain locally and do not travel far from their autumn feeding sites (Clarke *et al.* 1998).

During overwintering, adults aggregate in small groups of less than 20 individuals within a range of different shelters (Clarke *et al*. 1998). Adults have been found hibernating under the bark on trunks of trees and in cracks/splits of dead trees (Greaves 1966; Leon 1989), while Clark *et al.* (1998) identified 14 overwintering habitat types of which *Gahnia grandis* had the greatest mean number of insects and bracken fern litter sheltered the least (

Table 1). According to Clark *et al*. (1998), *Gahnia grandis* grasslands are by far the most important habitat for leaf beetle overwintering, however, Wardlaw (pers. comm. 2010) believes that *Poa* spp. (another type of grassland) is also an important overwintering site, although this has not been investigated.

Table 1: Habitats of overwintering P. bimaculata in the southern forests of Tasmania (Clarke *et al.* 1998)

Habitat description	No. sites sampled	% All sites sampled	Mean (± SE) no. live *C. bimaculata* collected per site	Mean (± SE) no. dead *C. bimaculata* collected per site	% All insects (live and dead) collected	Correlation between numbers of dead insects and total insects per site	% Sites occupied by live insects
Bracken fern[a] litter	7	1.81	0.14 ± 0.14	0.00	0.13	—	0.17
Moss	12	3.11	0.25 ± 0.13	0.33 ± 0.22	0.88	0.90*	0.25
Eucalypt litter	50	12.95	0.40 ± 0.11	0.36 ± 0.15	4.76	0.76*	0.26
Dogwood[b] litter	24	6.22	0.83 ± 0.33	0.45 ± 0.18	3.63	0.22 NS	0.45
Under bark of logs	28	7.25	0.89 ± 0.27	0.14 ± 0.11	3.63	0.36 NS	0.39
In manfern[c] crowns	27	6.99	0.93 ± 0.32	2.15 ± 0.81	10.40	0.93*	0.37
Under bark of stumps	52	13.47	0.94 ± 0.38	0.19 ± 0.10	7.39	0.15 NS	0.25
Cracks in standing myrtle[d] stags	26	6.73	0.96 ± 0.32	0.73 ± 0.31	5.51	0.67*	0.46
Under *Eucalyptus obliqua* bark	16	4.15	1.19 ± 0.75	4.06 ± 2.07	10.53	0.94*	0.31
Cracks in logs	35	9.07	1.40 ± 0.45	0.11 ± 0.07	6.64	0.08 NS	0.43
Under bark of eucalypt stags	10	2.59	1.70 ± 0.67	0.20 ± 0.13	2.38	0.15 NS	0.70
Cracks in fallen myrtle stags	11	2.85	2.27 ± 1.17	0.18 ± 0.12	3.38	−0.19 NS	0.45
Cracks in stumps	23	5.96	2.35 ± 1.02	1.17 ± 0.41	10.15	0.13 NS	0.39
Clumps of *Gahnia grandis*	65	16.84	3.31 ± 0.72	0.44 ± 0.16	30.58	0.15 NS	0.65

[a]Bracken fern, *Pteridium esculentum*; [b]dogwood, *Pomaderris apetala*; [c]manfern, *Dicksonia antarctica*; [d]myrtle, *Nothofagus cunninghamii*.
*$P < 0.01$; NS, not significant.

Predators and parasitoids together form the single most important factor affecting egg mortality (Figure 5), often completely controlling populations of *P. bimaculata* eggs and larvae (De Little 1990). The most common predators of *P. bimaculata* are two species of ladybird, the southern ladybird *Cleobora mellyi*, and the common spotted ladybird *Harmonia conformis* (Coleoptera: Coccinellidae)*;* the plague soldier beetle, *Chaultiognahus lugubris* (Coleoptera: Cantharidae); the tachnid flies *Anagonia rufifacies* and *Paropsivora sp.;* and a braconid *Eadya paropsidis* (Greaves 1966; Elliot *et al*. 1980; Elliott *et al.* 1992; Candy 1999). Birds are also considered predators of *P*. *bimaculata* (Greaves 1966), although their contribution to total mortality is unknown.

Figure 5: Predators of *P. bimaculata* including *Cleobora mellyi* and an unknown beetle species.

Both larval and adult ladybirds predate on *P. bimaculata* eggs and larvae (Greaves 1966) and, when combined with plague soldier beetles, can reduce populations by up to 80% (Elliott *et al*. 1992). The parasitoid flies lay small white eggs onto *P. bimaculata* that burrow into the chrysomelids' body when hatched (Greaves 1966). *Anagonia rufifacies* mainly attacks fourth instars. Whilst *Paropsivora* sp. has no preference for any particular instar (De Little 1982), the parasitised larvae do not die until after the fourth instar, when in their pre-pupal cells (Greaves 1966; Leon 1989). Parasitation of chrysomelids can be further complicated by hyperparasitism (Greaves 1966). The pupae and overwintering adults can also be attacked by pathogenic fungi of the genera *Beauveria* and *Metarhizium* (Candy 1999).

1.3 Paropsisterna bimaculata Integrated Pest Management

As there is no single environmentally acceptable control method, an Integrated Pest Management (IPM) system (termed the Leaf Beetle IMP) has been used to manage *Paropsisterna bimaculata* populations in Tasmanian plantation forests since the 1980s (Elliott *et al.* 1992; Candy 1999). Monitoring of pest eggs and larvae is conducted prior to significant defoliation taking place because it enables best estimates of likely defoliation, determines whether artificial control methods are required, and identifies the optimal timing for conducting pest control measures (Leon 1989; Elliott *et al*. 1992).

Temperature has a large effect on beetle natality and mortality with large populations occurring in years with above average summer temperatures (Greaves 1966). Increased temperature generally causes faster growth rates of *P. bimaculata* and growth of larger beetles, whilst larvae can be dislodged by extreme weather events such as high velocity winds, heavy rainfall or hail (Greaves 1966). Other environmental factors such as local soil type, previous foliage damage from insects, tree stress factors, and time since last fire can also be important in explaining herbivore spatial and temporal patterns (Clarke *et al.* 1997).

As *P. bimaculata* adults occur in small mobile aggregations, pest surveys need to be both regular (2 weeks apart or less) and intensive (sampling points within 150 m of each other) to confidently monitor populations (Clarke *et al.* 1997). Weekly

monitoring of egg and larval levels around the state should commence by mid-November and continue until February (Elliott *et al*. 1992; Elek 1997). Because *P. bimaculata* populations usually develop synchronously, with the larvae in the second instar 2 to 2 ½ weeks after egg-laying, it is relatively easy to predict a population's development (Leon 1989)

Elek (1997) found that if preferred tree species of *P. bimaculata* were interspersed in *E. nitens* plantations, then they could be used as early warning systems for monitoring beetle populations, and could also attract the beetles away from the *E. nitens* crop trees. Beetle numbers near roads are also good indicators of population levels within the plantation as adult beetles use roads as 'corridors' to move from one area to another, and are often found in high numbers along roadsides prior to moving within coupes (Jordan 2010, pers. comm.)

If monitoring is conducted and the number of *P. bimaculata* exceeds an economic threshold level of 0.3 Occupied Leaves per Shoot (OLPS), as determined by Candy (1999), then an appropriate management strategy is initiated (Elliott *et al.* 1992; Elek 1997). This usually involves the use of a broad-spectrum pyrethroid insecticide, cypermethrin (Elliott *et al.* 1992; Elek 1997; Candy 1999); although another biotic insecticide Novodor has been tested in laboratory and field trials as an alternative (Elliott *et al.* 1992; Candy 1999; Elek *et al.* 1999).

The active ingredient of Novodor FC® – the toxin of *Bacillus thuringiensis* subspecies *tenebrionis* (Candy 1999) – becomes toxic only after it is consumed because the insecticidal protein crystal damages the lining of the gut (Elek 1997). Novodor FC® does not harm beneficial insects and other non-target invertebrates as much as cypermethrin, but it is considerably more expensive and less effective (Baker *et al.* 2003**)**. However the use of cypermethrin requires greater operational controls, such as an increase in width of stream buffers, or increased distance from eagle nests, to minimise environmental impacts.

Elek (1997) found 50% of young larvae were killed within four days when sprayed with Novodor FC®, and a total of 90% were killed without completing their lifecycle. Although most young larvae were killed when sprayed with Novodor FC®, many older larvae survived but stopped feeding, most likely as a result of the

effects of sublethal doses (Elliott *et al*. 1992). Thus, if populations with asynchronous development occur then the effectiveness of Novodor FC® declines due to its low effectiveness against older larvae and adults (Elliott *et al.* 1992). Fortunately *P. bimaculata* populations mostly develop synchronously (Leon 1989). At low population levels of *P. bimaculata* in the field, the insecticide was found to cause similar levels of mortality over four days to natural predators (Elek 1997).

The Leaf Beetle IPM focuses on the importance of maximizing the effects of aerial insecticide spraying, while minimising the damage to natural predators and other organisms (Elliott *et al.* 1992). As high natural mortality occurs between the egg and 2nd larval instar stages, *P. bimaculata* levels can naturally decline by 95% prior to the end of the 4th instar (De Little 1990). Therefore it is important to ensure minimal harm befalls the natural predators of the coccinelid beetles, otherwise the use of insecticide could reduce the number of *P. bimaculata* predators, and hence increase their survival rate and consequent defoliation levels (De Little 1990; Elliott *et al*. 1992; Clarke *et al.* 1997)**.** Application of cypermethrin insecticide should take place after natural mortality controls such as predators have had a chance to kill most beetles, but prior to the start of the third and fourth instar when the majority (90%) of defoliation occurs (Greaves 1966; De Little 1990; Elliott *et al.* 1992; Clarke *et al.* 1997). Following any application of insecticide, a post-spray assessment of the population should be conducted to evaluate the effectiveness of the operation (Elliott *et al.* 1992).

Studies of alternative forms of control to insecticide spraying, such as the inundative release of coccinellid beetles and spraying of *P. bimaculata* eggs and early instars with spores of the entomopathogenic fungal genera *Beauveria* and *Metarhizium*, have recently been conducted but found impractical (Candy 1999). A study by Baker *et al*. (2003) found that although using augmentative releases of coccinelid beetles can reduce the numbers of *P. bimaculata* to below economically damaging levels in small areas, dispersal of coccinellids away from the site, and the costs associated with mass rearing, may make this approach unfeasible. Another potentially useful approach is to conserve or increase overwintering sites and food sources for coccinellids to build up their population numbers (Baker *et al*. 2003).

The Leaf Beetle IPM incorporates existing knowledge of *P. bimaculata* population dynamics and currently-preferred methods for controlling high numbers of beetles, however, this will undoubtedly change as new research and insecticide information becomes available (Elliott *et al.* 1992). Temporal and spatial patchiness also pose a problem to the Integrated Pest Management system, and further analysis of this needs to be undertaken.

1.4 Importance of spatial analysis techniques

Technologies such as Geographical Information Systems (GIS) and Remote Sensing (RS) are useful tools in managing pests as they are specifically designed to look at pests on a large spatial scale (Norton & Mumford, 1993). GIS and RS can be used for 3 main purposes (Norton & Mumford, 1993):

- To organise and store data.
- To manage and monitor resources and activities.
- To be used as a modelling and research tool.

GIS in pest management has been mainly used to look at large scale spatial dynamics such as insect migration, however, it can be used for pests with limited dispersal if they vary geographically due to local environmental conditions (Norton & Mumford 1993). GIS is used for either compiling data on where the pests are currently present or characterising the susceptibility of habitats to pest outbreaks (Liebhold *et al.* 1993). Computer modeling is also becoming increasingly important in developing pest management strategies. For example, GIS information can be used in predictive models to assess and predict species distributions and risks to biodiversity (Foody 2008). Predictive modeling is also important in determining the likely impacts of global climate change on pest biodiversity (Foody 2008).

Technologies such as GIS, remote sensing, and predictive modeling are likely to be increasingly used in pest management to maximize the effect but minimize the cost, both economically and environmentally, by providing increased knowledge of the pests and the environment in which they occur. These new strategies and techniques for pest management will hopefully lead to reductions in pest numbers, and thereby

increase productivity.

1.5 Aims and Objectives

Many environmental variables have been identified through previous studies to have a large impact on population numbers of *P. bimaculata*; however these variables are often highly correlated and no studies have been conducted to combine the various potentially-important factors together, or assess non-linear relationships. Moreover, little work has been done on factors affecting beetle abundances over large spatial scales. Further analysis of beetle distribution needs to be conducted at the large scales that are most relevant to management, thereby providing a better understanding of the beetle's ecology to improve management of the pests.

Wardlaw identified three important avenues of research that would provide information to limit economic losses in the future:

- Identify spatial patterns of egg and larval distributions within and among plantations to see whether an alternative method of monitoring plantations should be developed.
- Test the effectiveness of CABALA HEALTH in modelling *P. bimacualta* impacts on older plantations, and verify this using empirical data to determine whether financial benefits would be gained from extending monitoring into older coupes.
- Determine which landscape and site variables are significantly associated with variation in distribution of leaf beetles, to optimise the allocation of monitoring effort towards high risk areas.

Specific objectives of this study address the third of these research aims, and are to:

1. Quantify spatial landscape parameters that are considered potentially most important in influencing beetle numbers (aspect, curvature, hillshade, slope, sunlight index, and wetness index) from a fine-scale digital elevation model (DEM).

2. Quantify biological parameters that are considered potentially most important in influencing beetle numbers (planted year of plantation, species of *Eucalyptus*, distance to *Acacia dealbata*, distance to grasslands, distance to *Poa* grasslands, distance to tall eucalypt forest, distance to short eucalypt forest, distance to non-eucalypt forest, and distance to no forest).

3. Quantify climatic parameters that are considered potentially most important in influencing beetle numbers (average maximum summer temperature, average annual maximum temperature, annual rainfall, summer rainfall, number of days of rain, annual evaporation, average radiation) for Forestry Tasmania *Eucalyptus* plantations.

4. Quantify plantation shape parameters (area of coupe, perimeter length of coupe, and area/perimeter).

5. Develop predictive models for relationships between environmental variables and the distribution and abundance of *Paropsisterna bimaculata* in Eucalyptus Plantations across Tasmania (based on 2005 to 2010 data, but excluding the 2006/2007 season).

6. Assess the success of the predictive model using data from the current *P. bimaculat* beetle season (2010/2011).

7. Identify the most important variables that predict *P. bimaculata* distribution.

An almost unlimited choice of climatic, geographic, geological and forest husbandry variables was available for investigation. In order to reduce this to a manageable set, and minimise the chance of overfitting data with excessive covariates, factors investigated here were restricted to those suggested in the literature as potential drivers of population numbers of *P. bimaculata.* Thus, statistical analyses were undertaken in order to test *a priori* hypotheses. Support for these hypotheses requires both significant outcomes of statistical tests and also appropriate direction of change (e.g. a significant response of beetle numbers to altitude would not support the altitude hypothesis if numbers declined with altitude).

Hypothesis 1. Eucalypt plantations at highly productive sites have a higher occurrence of beetle outbreaks than in areas of lower productivity. New-season growth, which is soft and high in nitrogen, positively affects ovipositioning and *P. bimaculata* population dynamics (Clarke *et al.* 1997; Candy 1999). Consequently, productive sites where trees show rapid growth are predicted to have higher rates of beetle outbreaks than non-productive sites. I here test this prediction by assessing the importance on beetle outbreaks of factors that affect tree production: (i) Site Index (a measure of productivity used by Forestry Tasmania), (ii) mean annual rainfall over 30 year period, (ii) mean summer rainfall over a 30 year period, (iii) summer rainfall in year of beetle observations, (iv) average evaporation, (v) average rainfall/evaporation (vi) wetness index, (vii) curvature, (viii) aspect, (ix) slope. Beetle numbers are predicted to be highest at sights with high levels of moisture, and with a north-west aspect (Smith, 2000).

Hypothesis 2. Eucalypt plantations located close to beetle overwintering sites are more affected by beetle outbreaks than those further away. Grasslands are believed to provide the most important overwintering sites for *P. bimaculata* beetles, with *Gahnia grandis* Clark *et al.* (1998) and *Poa* spp. Wardlaw (2010, pers. comm.) suggested as particularly important. I here test the prediction that beetle outbreaks will be higher in close proximity to grasslands by assessing the importance on beetle outbreaks of (i) distance from nearest mapped grassland, and (ii) distance from nearest mapped *Poa* grassland. No broadscale data on the distribution of *Gahnia* were available, hence this potentially influential factor could not be assessed.

Hypothesis 3. Beetle outbreaks are affected by climatic factors. Population outbreaks of *P. bimaculata* usually occur in favourable weather conditions such as sunny days or high temperatures, and in unfavourable conditions they seek shelter (Greaves, 1966; Leon, 1989). Also, eggs and larvae can be dislodged from foliage by extreme conditions such as strong winds or hail (Greaves, 1966). I here test the prediction that climate factors influence *P. bimaculata* populations by assessing the importance of (i) incoming solar radiation, (ii) hillshade, (iii) mean annual maximum temperature over 30 year period, (iv) mean summer maximum temperature over a 30 year period, (v) mean summer maximum temperature in year of beetle observations, (vi) average

number of days with rain each year.

Hypothesis 4. Beetle outbreaks are affected by the shape and size of forestry coupes, as well as the species of *Eucalyptus* in the plantation. Roads act as transportation corridors for beetles with greater numbers of beetles occurring alongside roads than within coupes (Wardlaw and Jordan, pers. comm. 2010). Therefore coupes with large perimeter size to area potentially attract large numbers of beetles as there is greater access to the coupe. Beetle outbreaks differ between species of *Eucalyptus* in a plantation (Elek, 1997; Candy, 1999; Baker, 2002). I here test this prediction by assessing the importance of: (i) coupe area, (ii) perimeter, (iii) area/perimeter ratio, and (iv) *Eucalyptus* species.

Hypothesis 5. Beetle outbreaks vary in intensity between different Forestry districts and ages of plantations. Wardlaw (pers. comm. 2010) suggested that beetle outbreaks show greater variability in the district of Bass, compared to the rest of Tasmania, as Bass has a greater variability in elevation and landscape. Also, younger trees are preferentially attacked by *P. bimaculata* as the trees are still developing and have large amounts of flush foliage (Clarke *et al*. 1997; Candy 1999). I here test these predictions by assessing the importance of district, as well as age and planted year of plantations on *P. bimaculata* populations.

Hypothesis 6. Surrounding vegetation can disproportionately affect *P. bimaculata* beetle populations. Surrounding vegetation type can affect beetle populations by being less palatable than plantations, thereby drawing beetles to plantations. Alternatively, when surrounding vegetation is more palatable than the plantations, beetles could either be attracted away from plantations, or attracted in large numbers to the wider area (Smith, 2000). The presence of plant species such as *Acacia dealbata* that are important to *P. bimaculata* predators can also be of significance as defoliation appears to be less severe when plantations are grown with other species such as *Acacia dealbata* (Greaves, 1966). This study tests these predictions by looking at the importance on *P. bimaculata* of proximity to the forest groups: (i) tall eucalypt forests, (ii) short eucalypt forests, (iii) non-eucalypt forests, (iv) no forests, and(v) proximity to *Acacia dealbata*

Hypothesis 7. Beetle abundances are affected by elevation. Wardlaw and Jordan (pers. comm. 2010) suggest that populations of *P. bimaculata* increase with altitude. This study tests this hypothesis by assessing the impact of elevation on beetle numbers.

Population numbers of *P. bimaculata* vary greatly between years, possibly as a consequence of other unassessed annually-varying factors, such as defoliation damage from previous years. I take unassessed annual variability into account by looking at the importance of survey year on *P. bimaculata* populations.

Chapter 2 Data and Methods

2.1 Study Area

Tasmania is an island state of Australia, which covers over 64,000 km^2 (Cameron 1994). The environment varies significantly across this area with wide variation in altitude, water availability and soil fertility.

Geology

Tasmania is divided into two different general geology types. Western and North-eastern Tasmania are composed of extremely old igneous rocks, which are intensely folded and highly eroded. This region usually has relatively shallow soils that are acidic and possess low fertility (Reid *et al.* 1999). Central and South-Eastern Tasmania, however, are formed from much younger sedimentary rock with intrusions of igneous magma to form dolerite. This region has many faults. Tasmania has a large altitudinal range, with many mountain ranges and more than 60 peaks extending above 915 m (Reid *et al.* 1999).

Climate

The eastern half of Tasmania is relatively dry compared to western Tasmania. This is because moisture-laden winds from the west are forced upwards by mountain ranges, where they deposit most of their water load (Cameron 1994). The precipitation in the West ranges from 760 to 1750 mm or higher, whilst the East rainfall ranges from 500 mm to 800 mm (with the exception of 1200 mm in the north-eastern highlands). Temperature decreases with altitude, and although there is no permanent snowline, snow can form for several months on high peaks (Cameron 1994).

Vegetation

Tasmania has a high diversity of plant species. Much of Tasmania is dominated by *Eucalyptus* species, and the state is renowned worldwide for its tall eucalypt forests (Reid *et al.* 1999). Native eucalypts are generally divided into three broad categories; dry sclerophyll, wet sclerophyll and sub-alpine, however, these categories are not

discrete as they are characterised by ecotones.

Forestry Tasmania districts

Forestry Tasmania is responsible for 1.5 million hectares of state forest that covers 39% of Tasmanian forests (Forestry Tasmania). Forestry Tasmania divides Tasmania into 5 regions or districts—Bass, Derwent, Huon, Murchison and Mersey (Figure 6). Bass has the greatest number of coupes with almost the same total area of coupes as the other districts combined.

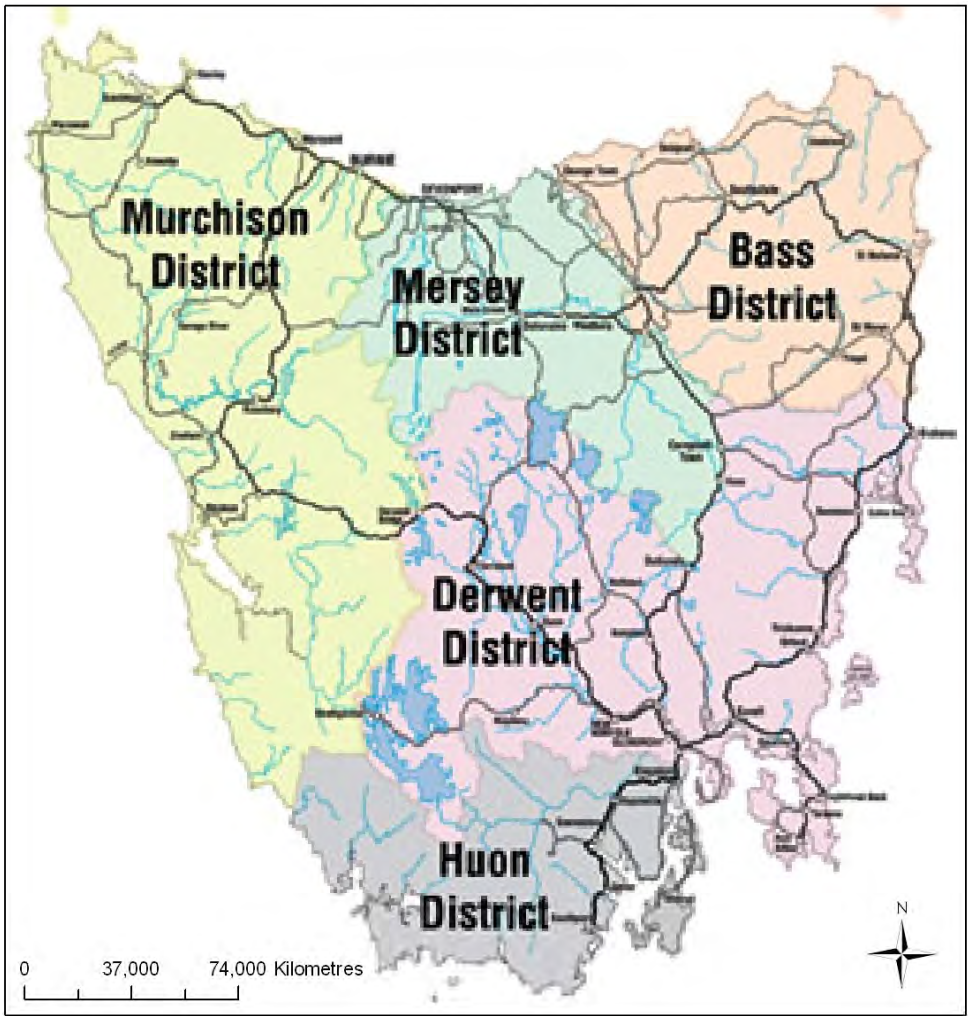


Figure 6: Forestry Tasmania districts

2.2 Data sets

2.2.1 *Paropsisterna bimaculata* counts

Paropsisterna bimaculata population data for monitored forestry coupes were made available by Forestry Tasmania for seasons between 2005/2006 and 2010/2011, however, the 2006 to 2007 season was not included in this analysis because large numbers of fires occurred during that summer, limiting monitoring and effective control of beetle populations (Wardlaw and Jordan, pers. comm. 2010), also, analysis of the most recent season's population numbers (2010 to 2011) was limited as these data were only compiled after most of the statistical analyses had already been completed.

Monitoring of juvenile *P. bimaculata* beetle numbers (eggs and larvae) is conducted by Forestry Tasmania on a weekly basis through the summer months, as this is when beetles are most active. Plantations of three to eight years of age are monitored as older trees are harder to monitor physically, and it is believed that older trees are targeted less frequently by *P. bimaculata* **(**Greaves 1966; De Little 1983). Juvenile beetle populations are assessed by Forestry Tasmania rather than adult beetles as adult aggregations can travel large distances in short time periods (Clarke *et al.* 1997); hence populations may go from high to low numbers between assessment and insecticide spraying. Monitoring is undertaken using a leaf beetle record sheet (Appendix 1) to calculate the rate of Occupied Leaves per Shoot (OLPS).

Initially a 'quick and dirty' visual analysis is conducted (first stage monitoring). This first stage assessment is based on a selection of ten roadside trees per coupe and a visual scan of these trees is conducted. If any evidence of larvae or eggs is present on a tree, even if it is only one organism, then the tree is recorded as occupied. Should the number of occupied trees be three or greater, a full site monitoring survey (second stage monitoring) is conducted, however if less than three trees are occupied, OLPS is recorded as zero. Roadside trees are used for the 'quick and dirty' analysis because roads act as transportation routes for beetles, with greater numbers of beetles present in roadside trees than within the coupe (Wardlaw and Jordan, pers. comm. 2010). Therefore the 'quick and dirty' analysis can generate an overestimate of beetle

numbers, and a lack of beetles roadside indicates a low likelihood of beetles further within the coupe.

A further 20 trees located within the coupe are randomly selected for second stage monitoring. Three shoots (branches) are removed from two different sides of each tree using pruning poles. A 'shoot' is defined as a terminal length of new season's growth of approximately thirty centimetres; identifiable by its thinner leaves that are a shiny lighter-red colour. The number of leaves with eggs or larvae is then recorded. For example, if a shoot has a leaf with one larva, and another leaf with 20 larvae, the recorded number is 2 occupied leaves on the shoot. This is repeated for the other 5 shoots from each tree. Because monitoring data show different OLPS readings though the season as a result of population fluctuations, the maximum OLPS rate is recorded for each coupe.

If a coupe should trigger the threshold OLPS of 0.3, then management of the coupe consists of either spraying populations, allowing natural mortality factors to reduce *P. bimaculata* numbers to acceptable levels, or not spraying due to operational reasons (such as adverse weather or proximity to wedge tailed eagle nests). In addition, following severe weather events, which could physically dislodge beetle eggs and larvae, follow-up monitoring is often conducted.

2.2.2 Forestry coupe maps

Forestry Tasmania has over 3126 *Eucalyptus* forestry coupes distributed across the state (Figure 7). Coupes are areas of forest used by Forestry Tasmania as the basis for integrating operational, tactical and strategic wood production planning (Smith, 2000). A GIS polygon layer including all the forestry coupes, each labelled with an identification code, such as AR022H, was provided by FT. This layer was entered into a GIS database, allowing calculation of the area of each coupe and perimeter length.

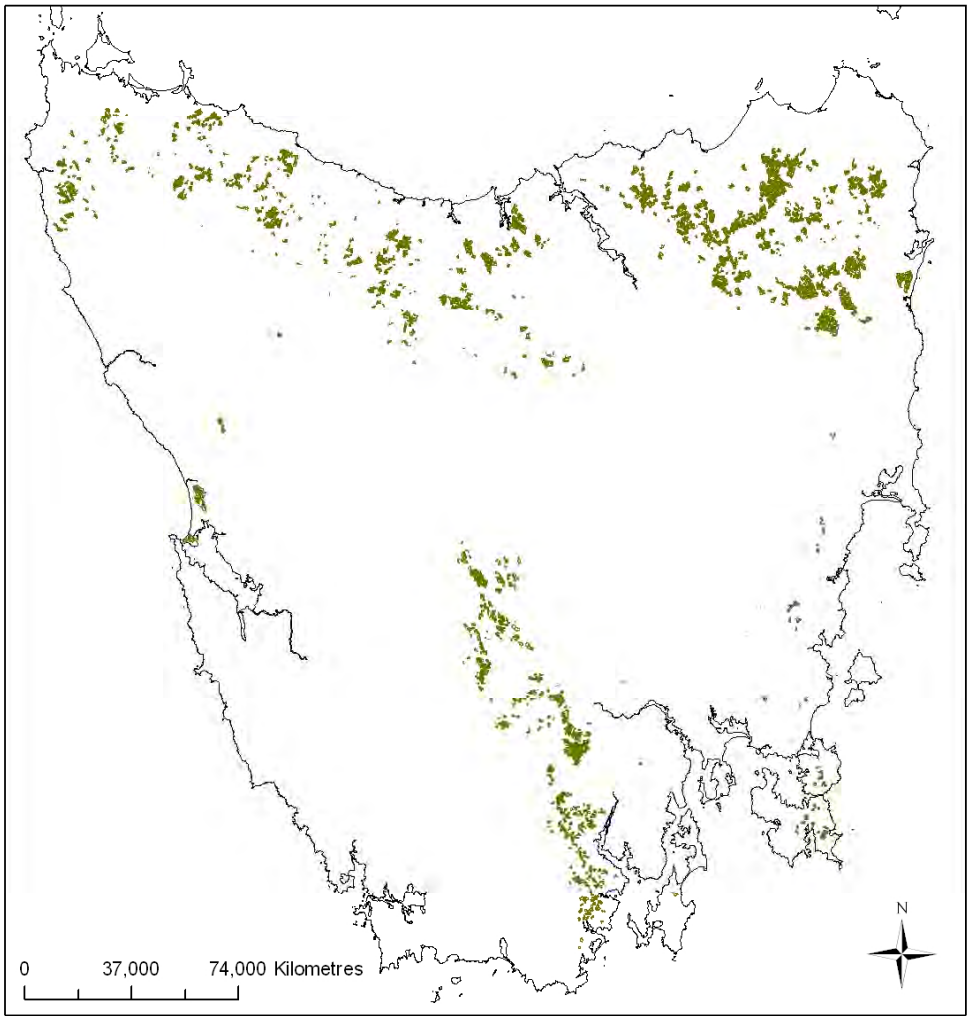


Figure 7: Forestry Tasmania eucalypt plantation coupes across Tasmania.

2.2.3 Non-derived data sets from forestry

Along with the maximum OLPS recorded for each coupe, Forestry Tasmania also provided other physical data for each coupe including: species of *Eucalyptus (nitens* or *globulus*), site index (SI), age of coupe when harvested, year of coupe plantation, surveyed year, district, summer maximum temperature, annual maximum temperature, annual rainfall, summer rainfall, number of raindays, annual evaporation, and average evaporation. Site index is an estimate of mean dominant height at 50 years of age (Elliot *et al.* 2003). The climate data have been calculated as a 30 year average for the base period 1961-1990 .

2.2.4 Digital Elevation Model (DEM) and derived data sets

DEM

A Digital Elevation Model (DEM) for Tasmania at 25 m resolution (Figure 8) was supplied by Forestry Tasmania and was accurate to 25 m for most of the state, except for the southwest where accuracy declines but no forestry coupes were present. From this DEM several physical parameters were derived.

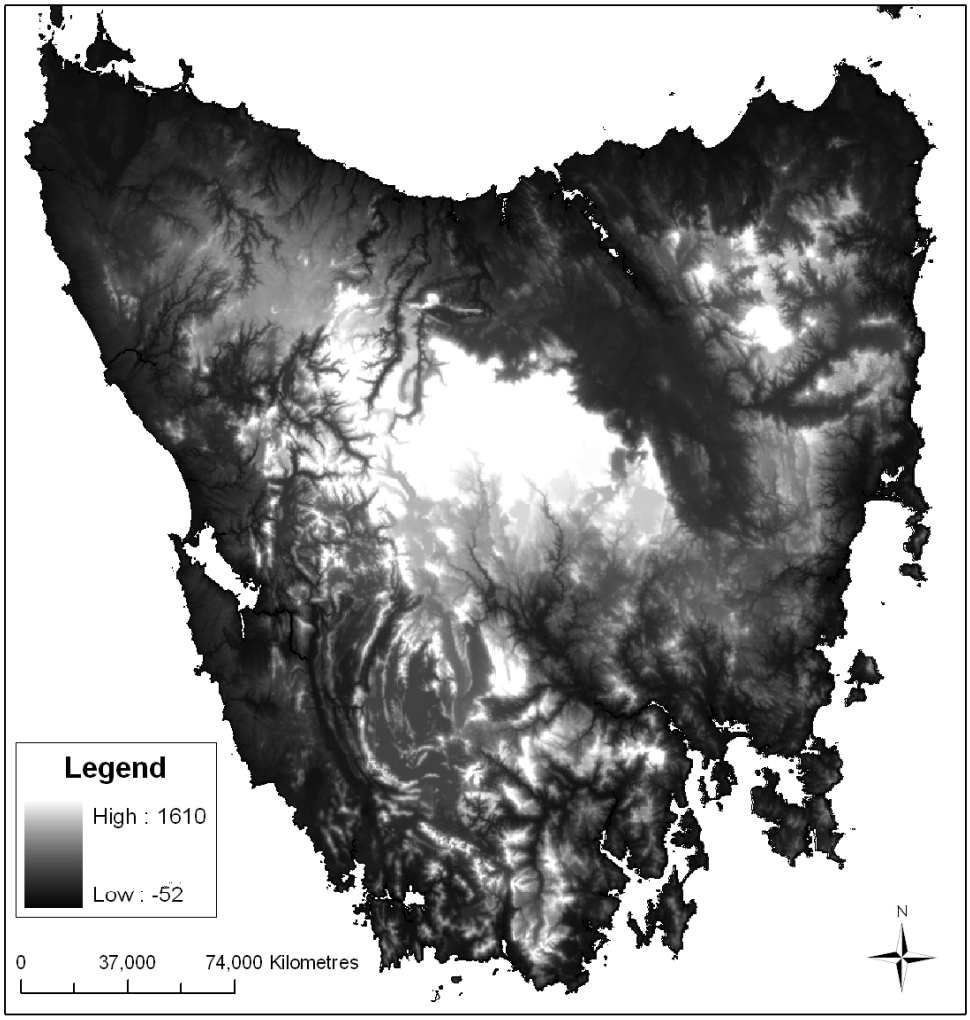


Figure 8: Digital Elevation Model (DEM)

Slope

The slope function identifies the steepest downhill gradient for any given surface by identifying the rate of maximum change for each cell in the DEM using the average maximum technique. Slope is calculated by identifying the maximum rate of change between a cell and any of its eight neighbors in a 3 by 3 grid matrix. Low output slope value indicates a flat terrain, and as the output value increases so does the steepness of terrain. Cells located in a neighborhood with a no data z-value are allocated the z-value for the centre cell. Edge cells have three neighboring cells with no data, and are each assigned the same value as the centre cell. This tends to lead towards a flattening out of slopes around the DEM periphery. Slope is an important variable because of its influence on runoff, soil drainage and erosion.

Aspect

Aspect was determined to be an important variable for *P. bimaculata* populations as Smith (2000) found higher populations on North-West facing slopes. Aspect is calculated in a similar way to slope using the steepest gradient, however, for this metric the direction that the plane faces is the output raster for each cell. Aspect determines the direction that the maximum rate of change in value from one cell to its neighbors (greatest slope) occurs. The resulting aspect values are the same as compass directions, from 0 (due North) around the circle to 360 (also due North). All flat areas (i.e. areas with a slope of 0) are assigned an aspect of -1. Aspect was reclassified to discrete compass directions (Table 2).

Table 2: Reclassification of aspect

Angle	Reclassified	Direction
-1	1	Flat
0-22.5	2	North
22.5-67.5	3	North-East
67.5-112.5	4	East
112.5-157.5	5	South-East
157.5-202.5	6	South
202.5-247.5	7	South-West
247.5-292.5	8	West
292.5-337.5	9	North-West
337.5-360	2	North

Curvature

Curvature is the second order derivative of a surface, or the slope of the slope, and expresses the degree of curvature of the terrain. Curvature affects the acceleration or deceleration of flow in the profile direction across a surface and it indicates a convergence or divergence of flow in the planar direction. A positive curvature indicates the surface is upwardly convex at that cell, a negative curvature indicates the surface is upwardly concave at that cell, and a value of zero indicates the surface is flat. The curvature derivative can provide valuable information about the local exposure and hydrological characteristics of a landscape.

Hillshade

Hillshade is calculated by determining the hypothetical illumination for any given location. A hypothetical light source is set and each cell's illumination is calculated in relation to its neighboring cells. An azimuth and elevation angle need to be set to determine the direction the light comes from. The azimuth is the angular direction of the sun and varies from 0 (North) around the compass to 360 (North again). The default azimuth for hillshade is 315 (North West). The elevation angle is the angle above the horizon that the illumination comes from, varying between 0° (on the horizon) and 90° (the zenith, or the direction straight up). The default angle of illumination is 45°. Hillshade is displayed on maps in shades of grey associated with integers varying from 0-255. As the values increase the hillshade gets lighter, with 0 being black, and 255 being white. Modelling the spatial distribution of Hillshade to assess its relationship to *P. bimaculata* is important as the beetles are found to occur in higher numbers and grow faster with warmer temperatures (Greaves 1966).

Incoming solar radiation

Topography is the major factor modifying the distribution of incoming solar radiation (insolation) at the local landscape scale. Variability in elevation, surface orientation (slope and aspect), and shadows cast by topographic features create local variability in insolation. This leads to high spatial and temporal heterogeneity in the local energy and water balance, which in turn affects soil temperature, evaporation, snow melt patterns, and soil moisture. It is therefore important to compare the

spatial distribution of solar radiation with *P. bimaculata* populations as the beetles are found to be in higher numbers on sunny days, and with warmer temperatures (Greaves 1966).

In a GIS, area-based solar radiation models compute insolation from the surface orientation and shadow effects from a digital elevation model (DEM). Area solar radiation analysis was used to calculate the insolation across the entire DEM. As the study area is so large the calculations were repeated for smaller areas and amalgamated to produce an insolation map for the entire geographic area. The azimuth had to be set from its default setting of 134 (South East) to 314 (North West) as we are in the Southern Hemisphere, and an annual average was calculated.

Wetness index

The wetness index is calculated from a flow direction network and a slope layer, both derived from a DEM. The flow direction network shows the flow direction for each grid cell and based on this layer the upstream area for each cell can be calculated. The wetness index is a function of the upstream area and the slope, whereby the greater the upstream area and the flatter the cell the higher the wetness index. The wetness index only provides a hypothetical surface wetness (unitless index) without taking into account soil properties or geological characteristics.

The wetness index (also known as Topographic Wetness Index is calculated using the following expression where a is specific catchment area (upslope contributing area), and S is the slope in degrees (Bohner 2006).

$W = ln(a/tan(S))$

The specific catchment area is defined as the corresponding drainage area per unit contour width ($m^2\ m^{-1}$) and is calculated using the multiple flow direction method (Freeman, 1991). The Topographic Wetness Index shows the likelihood of a cell producing runoff as areas with high moisture contents are prone to saturation. The greater the value of a cell, the higher the likelihood of the area being prone to saturation or overland flow. Wetness index is important in assessing beetle

populations as it has a high correlation with productivity.

Data sets derived from TasVEG

Vegetation community data were based on TasVEG, which was obtained from The LIST. TasVEG is a Tasmania-wide vegetation map, produced by the Tasmanian Vegetation Mapping Program (TVMP) as part of the Department of Primary Industries, Pollution, Water and Environment (DPIPWE). TasVEG includes 154 different vegetation communities for across Tasmania, at a scale of 1:25,000 (TVMP, 2011). Grasslands (Lowland grassland complex, Coastal grass and herbfield, Highland Poa grassland, Lowland *Poa* grassland, Rockplate grassland, Lowland sedgy grassland, Lowland Themeda grassland) were selected from TasVEG using an SQL query due to their potential as overwintering sites for *P. bimaculata,* and a proximity analysis was then conducted using Euclidian distance. This was repeated for *Poa* grasslands (Highland *Poa* grasslands and lowland *Poa* grasslands**),** also a potential overwintering site, and *Acacia dealbata* forest due to their potential to host *P. bimaculata* predators. Although TasVEG is relatively accurate, the species composition of the understorey vegetation is not specified in the map unit, so is only as accurate as the broad vegetation classes included.

2.2.6 Data sets derived from Forest group

ForestGroup was a GIS vector layer obtained from Forestry Tasmania that contained data on forests surrounding the plantations. This study focused on four different types of forest groups, namely tall eucalypt forests (for_tall), short eucalypt forests (for_low), non-eucalypt forests (including: Tasmanian Blackwood, Tasmanian Oak, Myrtle, Celery Top, Huon Pine, Silver Wattle, Clear and Black-Heart Sassafras, other pines, and rainforest) (for_non), and areas with no forest (for_less). These variables were chosen due to their potential to influence *P. bimaculata* numbers by attracting beetles an area, or making an area unattractive, and were analysed in the same way as the TasVEG variables, by using a SQL query and proximity analysis.

2.2.7 Climate data derived from BOM

Monthly Rainfall and temperature data for Australia were obtained from the Bureau of Meteorology (BOM) for November 2005 to February 2011 (excluding Nov. 2006-

Jan. 2007). This was then converted from ASCII to Raster format, the coordinate system defined as GDA94 UTM zone 55, and made to fit the same extent as the DEM (Tasmania). The three summer months for temperature for each season were averaged using raster calculator, whilst for Rainfall they were summed as average rainfall over the season. Rainfall and climate are both important in assessing *P. bimaculata* populations as climate variables have such as strong influence on their lifecycle.

2.3 GIS processing methods (Data processing)

The data set contained several plantations that were sampled in more than one year. They were treated as separate plantation sample events for the purpose of the analysis. Variables such as OLPS, age of plantation, surveyed year, yearly summer rainfall and yearly summer temperature changed each season, however, the remainder of the variables remained constant each year.

Summary statistics were applied once the data layers had been created from the DEM, TasVEG, ForestGroup, and BOM data layers, which allowed the mean result for each variable in each coupe to be obtained using the coupe polygons in a zonal mean statistic operation. These were then compiled into one data file and spatially joined to the GIS polygon coupe layer, along with the OLPS records and other non-derived data.

2.4 Statistical analyses

The Random forests (RF) algorithm (Breiman, 2001) is a powerful non-parametric statistical modelling tool that has been rarely applied in ecology, however, it is widely used in other disciplines such as bioinformatics (Cutler *et al.*, 2007). Individual regression trees are commonly used for statistical modelling in ecology for building explanatory or predictive classification or regression models. Random forests use an ‘ensemble’ approach that combines multiple regression or decision trees, generally at least 500, to produce a more accurate model (Pitcher *et al.* 2004). Each regression tree produces a number of splits or nodes that are increasingly homogenous to the class variable, as measured by the Gini index (Cutler *et al.* 2007; Pal, 2005). This splitting of the ‘tree’ continues until further subdivisions cease to

reduce the Gini index. This final node is called the terminal node, and the regression tree is said to be fully grown (Cutler *et al.* 2007). Individual regression trees are constructed by applying a random selection with replacement of observed values in the data set, also known as a bootstrap sample. Two-thirds of the data is used for training purposes and one-third is used for cross-validation and results in the out of bag error (OOB-error). This OOB-error metric can be used to assess the performance of the model. This approach is known as bootstrap aggregation or 'bagging'.

Variable importance scores can also be calculated using the OOB cross-validation data. The importance of variable *v* is the percent increase in the OOB mean sum-of-squared errors when the values of *v* are randomly permuted. The partial effects of each predictor can be calculated by integrating the estimates with respect to each predictor individually (Haywood *et al.* 2007; Pitcher *et al.* 2004). Partial dependency plots are also important products of random forests and give a graphical depiction of the marginal effect of a variable on the class probability (classification) or response (regression).

The approach used by random forests to assess important predictor variables has advantages compared with other statistical classifiers. These advantages include:

- a very high classification accuracy,
- an ability to model complex interactions between predictor variables,
- an ability to model several types of statistical analysis including classification, regression, clustering, multi-dimensional scaling, survival analysis, and unsupervised 'machine learning',
- an algorithm for imputating missing data.

Although random forests can be used to undertake several types of statistical analysis, in this study the focus was on using this method as a classifier to model and predict OLPS classes. Additionally, the random forest technique was used for calculating variable importance of each input variable to the prediction of OLPS allowing an exploration of the importance of environmental factors to beetle infestation. Finally, random forests allow generation of partial dependence plots for

the most important variables to determine how they are correlated with beetle populations. Because the random forests method can accommodate collinear data, a total of 33 covariates were used based on the hypotheses outlined in section 1.4 (In this study, the random forests technique was used as a classifier rather than a regression tree, therefore the explanatory variable, OLPS, needed to be categorised. The OLPS score was binned from a continuous variable into a discrete variable on the basis of OLPS scores recorded as less than 0.3 (threshold level), or equal to and greater than 0.3. OLPS scores above 0.3 could not be subdivided further because coupes above the threshold may have been sprayed, and thus might not have met their potential maximum in terms of beetle numbers. Therefore, mixing sprayed and unsprayed coupes in comparisons would have biased the results.

Table 3**).** The random forest implementation in the 'Rattle' data mining package for R[1] was used to generate the results.

In this study, the random forests technique was used as a classifier rather than a regression tree, therefore the explanatory variable, OLPS, needed to be categorised. The OLPS score was binned from a continuous variable into a discrete variable on the basis of OLPS scores recorded as less than 0.3 (threshold level), or equal to and greater than 0.3. OLPS scores above 0.3 could not be subdivided further because coupes above the threshold may have been sprayed, and thus might not have met their potential maximum in terms of beetle numbers. Therefore, mixing sprayed and unsprayed coupes in comparisons would have biased the results.

[1] http://rattle.togaware.com/

Table 3: Predictor covariates

Predictor Variable	Code	Source
Elevation	DEM	Forestry Tasmania/theLIST
Slope	Slope	Derived from the DEM
Aspect	Aspect	Derived from the DEM
Hillshade	Hillshade	Derived from the DEM
Curvature	Curvature	Derived from the DEM
Incoming solar radiation	Sunlight	Derived from the DEM
Wetness index	Wetness	Derived from the DEM
Species of eucalypt	Species	Forestry Tasmania
Plantation survey year	survey_year	Forestry Tasmania
Site index	SI	Forestry Tasmania
Age of plantation when surveyed	Age	Forestry Tasmania
Year of plantation	Planted year	Forestry Tasmania
Forestry district	District	Forestry Tasmania
Area of coupe (hectares)	Area_ha	Forestry Tasmania
Perimeter of coupe	perimeter	Forestry Tasmania
Area of coupe/perimeter of coupe	Area_perim	Forestry Tasmania
Distance to acacia stands	Acacia	Derived from TasVEG
Distance to poa grasslands	Poa	Derived from TasVEG
Distance to grasslands	Grass	Derived from TasVEG
Average distance to tall eucalypt forests	For_tall	Derived from VEGGROUP
Average distance to short eucalypt forests	For_low	Derived from VEGGROUP
Average distance to non-eucalypt forests	For_less	Derived from VEGGROUP
Average distance to non-forests	For_non	Derived from VEGGROUP
Average radiation	Ave_rad	BOM (1961-1990 average)
Average annual rainfall	Annual	BOM (1961-1990 average)
Average annual evaporation	Annual_evap	BOM (1961-1990 average)
Average annual maximum temperature	Annual_max	BOM (1961-1990 average)
Average annual rainfall/evaporation	Rain_evap	BOM (1961-1990 average)
Average number of days with rain each year	Raindays	BOM (1961-1990 average)
Average summer rainfall	Summer	BOM (1961-1990 average)
Average summer maximum temperature	Summer_max	BOM (1961-1990 average)
Actual summer rainfall	Rainfall_2	BOM (Annual summer data)
Actual summer maximum temperature	Summer_max_2	BOM (Annual summer data)

Models were created using random forests with each of four sets of climate data for each of the following combinations of districts:

- All four seasons for all districts
- All four seasons for Bass only, and
- All four seasons for all districts except Bass (Derwent, Huon, Murchison, and Mersey)

In this study, all districts excluding Bass are classified together as a separate category because Wardlaw (pers. comm., 2010) believed Bass to be anomalous in terms of greater patchiness of beetle outbreaks than the other districts.

The four different climate combinations were assessed because of the need to derive models based on long-term historical data that can be used in a predictive sense, and also data that relate beetle outbreaks to rainfall records compiled over the same period as the outbreak. Summer rainfall and maximum summer temperature during the weeks preceding beetle outbreaks have been suggested in the literature as particularly important when trying to understand which climate variables most strongly affect beetle outbreaks (Greaves, 1966; Clarke *et al.* 1997). When predicting outbreaks for future summers, it is clearly not possible to include data on rainfall for summers yet to come to derive model predictions, other than in a general sense with, for example, forecast trends associated with global climate change. Non-climate metrics (i.e. DEM-derived, habitat and forest husbandry metrics) were included in all models. The four climate combinations assessed using random forests were:

1. 30 year mean (1961-1990) for all climate data plus summer rainfall and mean summer maximum temperature for the actual summer of beetle counts
2. 30 year mean for summer rainfall and summer maximum temperature but no other climate data
3. No climate data other than summer rainfall and mean maximum temperature in the summer of beetle counts

4. 30 year mean for all climate data such as raindays, average evaporation, summer rainfall, temperature.

When assessing the accuracy of each random forest model combination of climate and district, two different methods were used. Either the model was created using two-thirds of the data and validated with one-third of the data, or the model was created using all the data and validated using a separate file with separate validation data. An example of this is using the data from the 2007/2008 to 2009/2011 seasons for RF training and validating it using a separate file containing the 2005/2006 beetle data.

For each of the random forests modeled using the above parameters a variable importance plot was created. These plots helped to assess the hypotheses by determining which variables had the greatest correlation with *P. bimaculata* outbreaks. The most important variables, as determined by the variable importance plots were then used to create partial dependency plots.

Different combinations of districts, climate, and seasons were used to create and validate the data and an error matrix for each was created (example below). An error matrix, also known as a confusion matrix shows the true outcomes and compares them against the predicted outcomes for the model. Two tables were created showing the count of observations and the percentage of observations for each class. The cells of the error matrix from left to right, top to bottom are referred to as a) True Positives, b) False Positives, c) False Negatives, and d) True Negatives. The error matrix also shows an overall error for the model (e), indicating the number of correctly classified samples divided by the total number of samples (between 0 and 1).

Error matrix for the Random Forest model [validate] (counts):

		Actual	
		Above 0.3	below 0.3
Predicted	above 0.3	a	b
	below 0.3	c	d

Error matrix for the Random Forest model [validate] (%):

		Actual	
		Above 0.3	below 0.3
Predicted	above 0.3	a	b
	below 0.3	c	d

Overall error: e

The error matrix was used in this study to determine if the model would be accurate at predicting *P. bimacula* beetle populations. The probability of having a false negative, i.e. predicting a beetle population to be below the OLPS threshold that was actually above threshold was also of importance as the costs associated with obtaining a false negative (a coupe that should have been sprayed but was not), is much higher than the amount saved by not monitoring (Table 4). For example the incurred loss for a false negative is -$119.95 per hectare, and the cost of monitoring is $10.2 per hectare. So if 11 coupes were monitor it would cost $112.20, however if monitoring wasn't done payment of monitoring costs wouldn't occur, but even only one outbreak would incur a loss of $119.95 per hectare.

Table 4: Costs associated with beetle monitoring and control

	Mean	95% CI
Incured loss $/ha	-119.95	14.11
Monitoring $/ha	10.2	0.49
Averted value $/ha	189	21.8
spraying $/ha	44.6	1.75
Coupe area (ha)	37.3	2.09

Once the most effective model was determined from the accuracy assessment then the relative frequency scores for this model were obtained. The scores showed the relative frequency of validation data entries being a true positive, false positive, true negative or false negative. If the relative frequency is set as 0.5 then any score above this shows the probability of a coupe being under 0.3 as less than 50% and it is classed as over threshold. Increasing the relative frequency to 0.75 or 0.9 increases the cut-off for the probability of a coupe being under-threshold, thereby reducing the probability of a coupe being over threshold (reducing the false negatives), but increasing the true and false positives, and thus the number of sites that need monitoring. The scores and associated costs were assessed to determine whether models would be cost effective for use by Forestry Tasmania.

2.5 General map layers for two most important variables

As discussed in further detail in the Results section, beetle populations decreased sharply after 10 km distance from *Poa* and below 500 m altitude (section 3.3.4); consequently, a 10 km buffer was created around *Poa* grasslands and elevations above 550 m were selected using conditional parameters in single map algebra. These outputs were then used to form a layer showing relatively high and low likelihoods of beetle infestations. The purpose of creating these layers was for generalised use for forest managers in determining where high or low populations were likely to occur.

Chapter 3 Results

3.1 Paropsisterna bimaculata count results

3.1.1 Coupe data and OLPS results from forestry

The number of coupes in each district per year is recorded in Table 5 and percentage in Table 6, however, thirty-two records from the 2010/2011 season were ignored as no corresponding climatic data were available. The number of coupes surveyed for beetle outbreaks gradually increased over the years the study was conducted, with Bass having the greatest number of coupes investigated each year.

Table 5: Number of coupes monitored per district per year

	All years	2005/ 2006	2007/ 2008	2008/ 2009	2009/ 2010	2010/ 2011
all districts	2608	395	494	408	573	738
Bass	870	163	249	199	259	334
Derwent	197	52	42	36	67	110
Huon	228	50	62	45	71	73
Mersey	171	48	43	30	50	48
Murchison	404	82	98	98	126	173
ex_Bass	1000	232	245	209	314	404

Table 6: Percentage of all coupes monitored in each district per year

	All years	2005/ 2006	2007/ 2008	2008/ 2009	2009/ 2010	2010/ 2011
all districts	100	15	19	16	22	28
Bass	46	6	10	8	10	13
Derwent	12	2	2	1	3	4
Huon	12	2	2	2	3	3
Mersey	8	2	2	1	2	2
Murchison	22	3	4	4	5	7
ex_Bass	54	9	9	8	12	15

The number of coupes with an OLPS of greater than 0.3 increases over time, with 2010/2011 having the highest number with 249 coupes and 2005/2006 having the lowest number with 121 coupes (Table 7). However, this is also related to increasing number of coupes in total, so it is more accurate to look at the results as a percentage (Table 8). The 2008/2009 season has the highest proportion of coupes with an OLPS of greater than 0.3 (38%), followed by 2010/2011 (34%) and 2005/2006 (31%),

however, the percentage of coupes with an OLPS greater than 0.3 fluctuated relatively little between years. In comparison the percentage of coupes with an OLPS of 0 decreased markedly over time, and the number with between 0 and 0.3 increased by about the same amount (Figure 9).

Table 7: OLPS scores in each category of 0, 0-0.3, and 0.3 or greater by year

	0	0-0.3	0.3+	Total
All years	1191	598	819	2608
2010/2011	101	388	249	738
2009/2010	276	136	161	573
2008/2009	235	16	157	408
2007/2008	317	46	131	494
2005/2006	262	12	121	395

Table 8: Percentage of OLPS scores in each category of 0, 0-0.3, and 0.3 or greater by year

%	0	0-0.3	0.3+
2010/2011	14	52	34
2009/2010	48	24	28
2008/2009	58	4	38
2007/2008	64	9	27
2005/2006	66	3	31

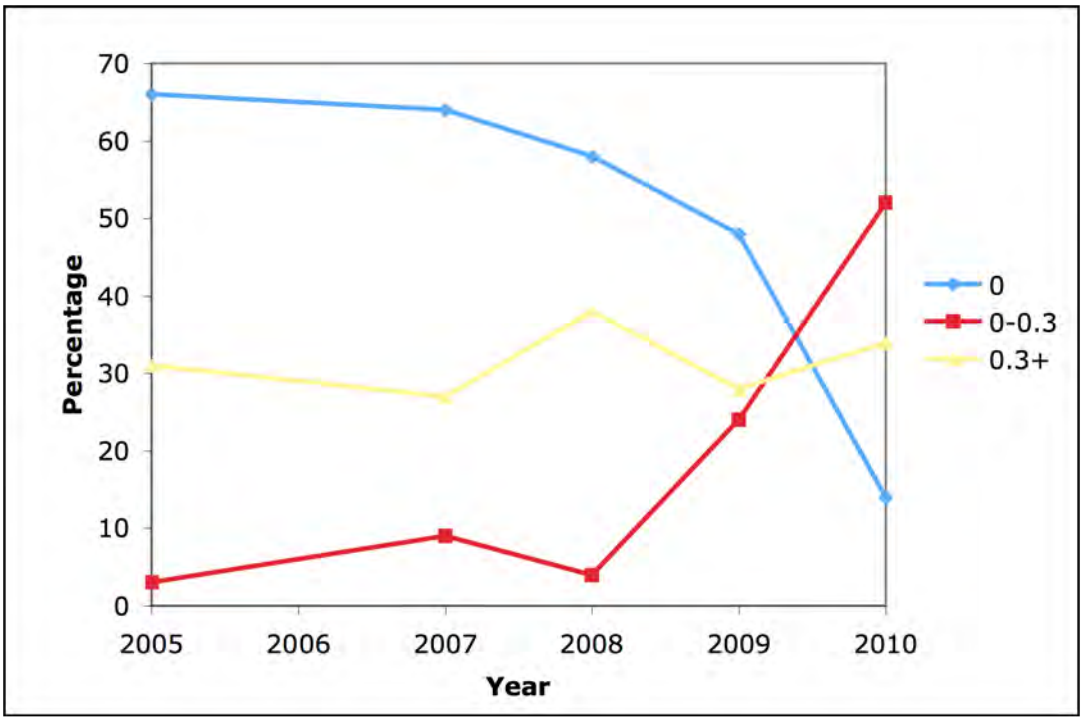


Figure 9:Percentage of coupes with OLPS of 0, 0-0.3 and 0.3+ over 5 seasons (2006 season excluded).

3.1.2 Annual OLPS rates in coupes over five years

OLPS rates for all the coupes in the state that were monitored in 2005/2006, 2007/2008, 2008/2009, 2009/2010 and 2010/2011 are shown in Figures 10-14, respectively. Visual inspection of data suggests that the 2008/2009 season was characterised by the greatest percentage of above average beetle populations, but was concentrated in the north-east; whereas the results for 2009/2010 were more widespread. However, as the sample size is so large, and covers such a large distribution it is difficult to make generalised assumptions from visual analysis of the results.

3.2 Derived data sets

Data sets derived using GIS included landscape layers (slope, aspect, curvature, hillshade, incoming solar radiation, and wetness index); vegetation proximity layers (proximity to general grasslands, proximity to *Poa* grasslands, proximity to *Acacia dealbata*, proximity to tall eucalypt forests, proximity to short eucalypt forests, proximity to non-eucalypt forests, and proximity to areas of no forest all); and annual climate data layers (mean maximum summer temperature and mean summer rainfall). They are included in Appendix 2 and were used as some of the input variables for the Random forests models.

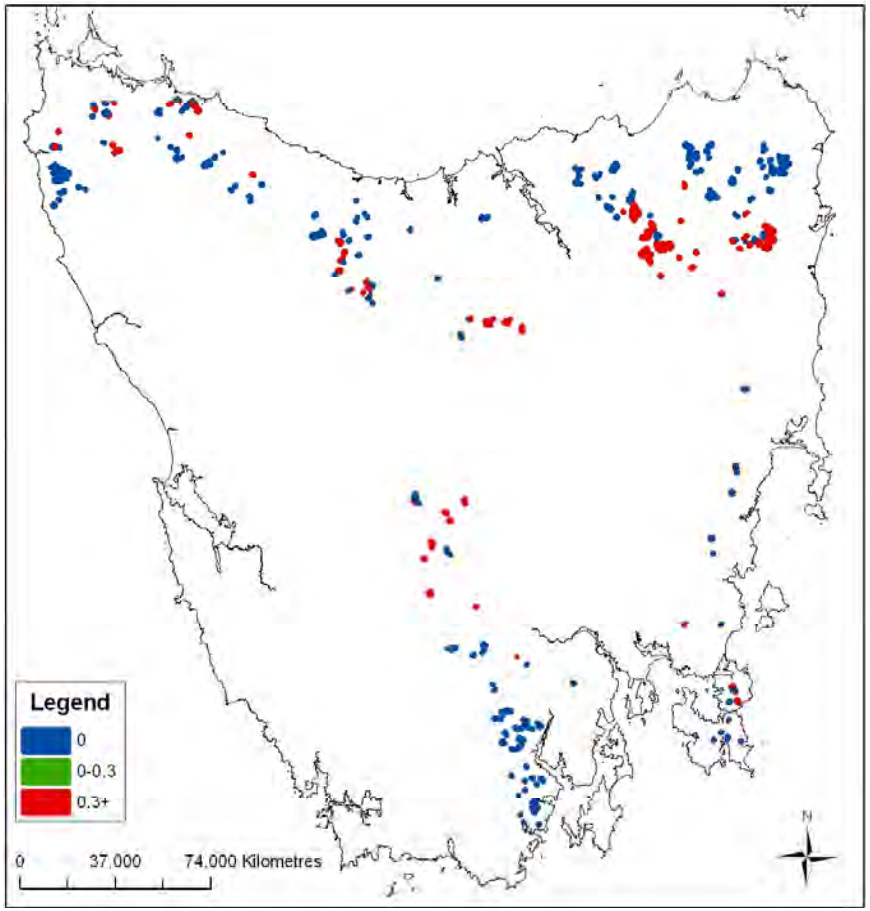


Figure 10: *P. bimaculata* beetle populations for the 2005/2006 season

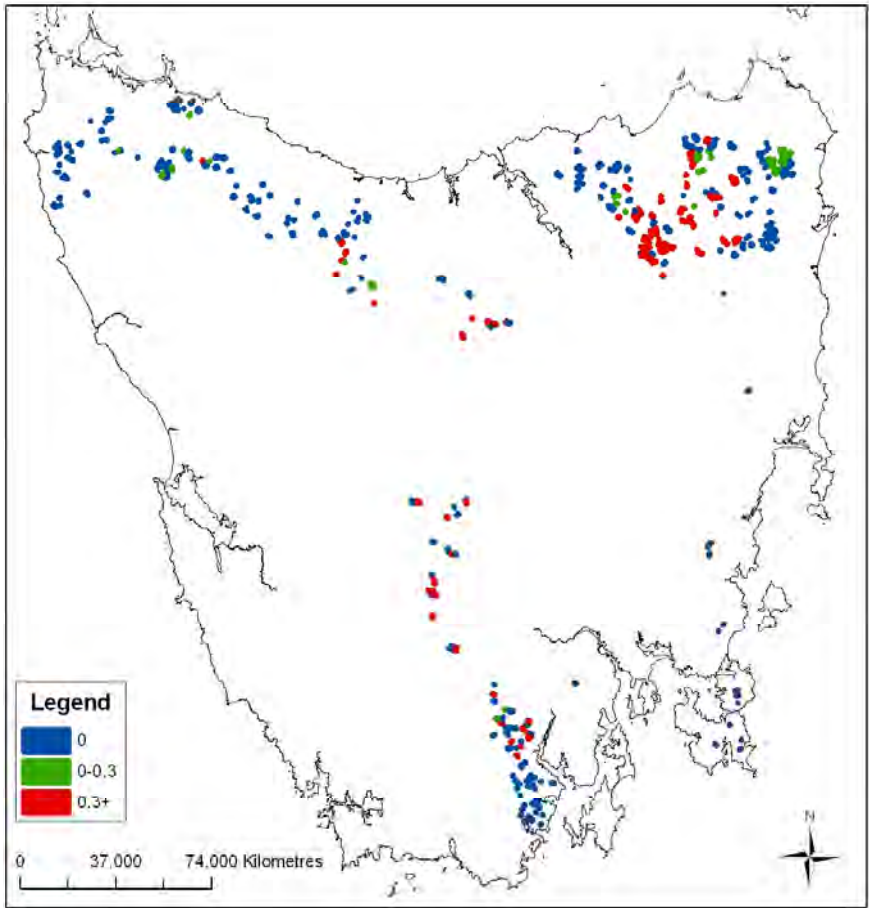


Figure 11: *P. bimaculata* beetle populations for the 2007/2008 season

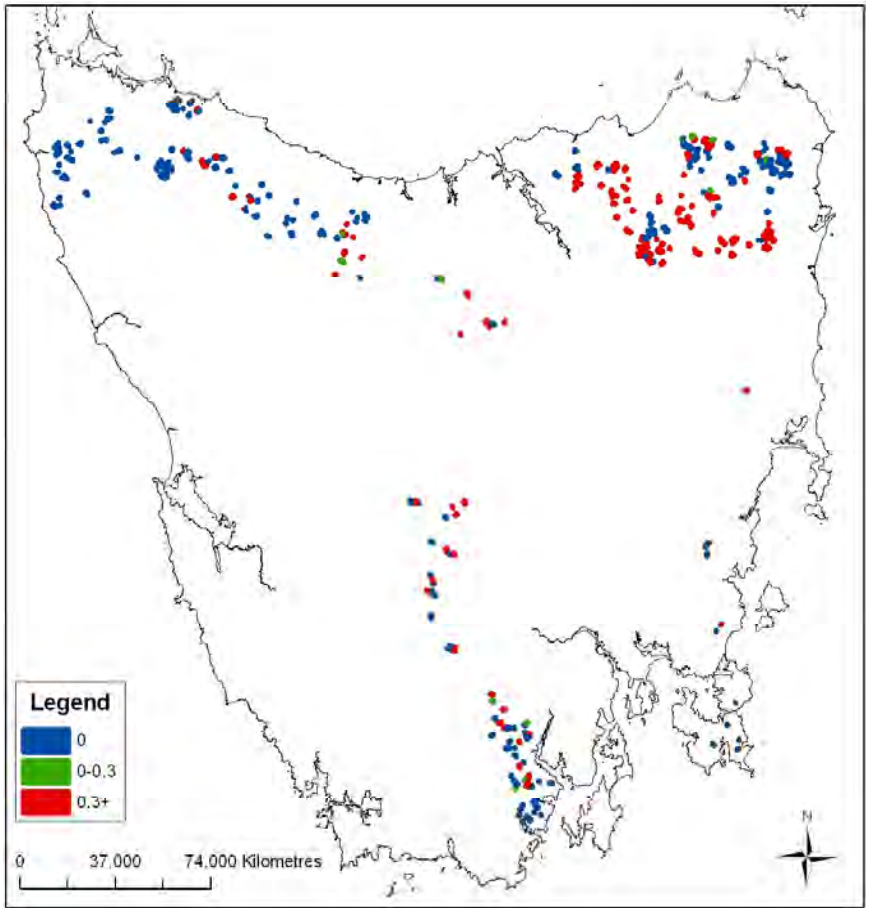


Figure 12: *P. bimaculata* beetle populations for the 2008/2009 season

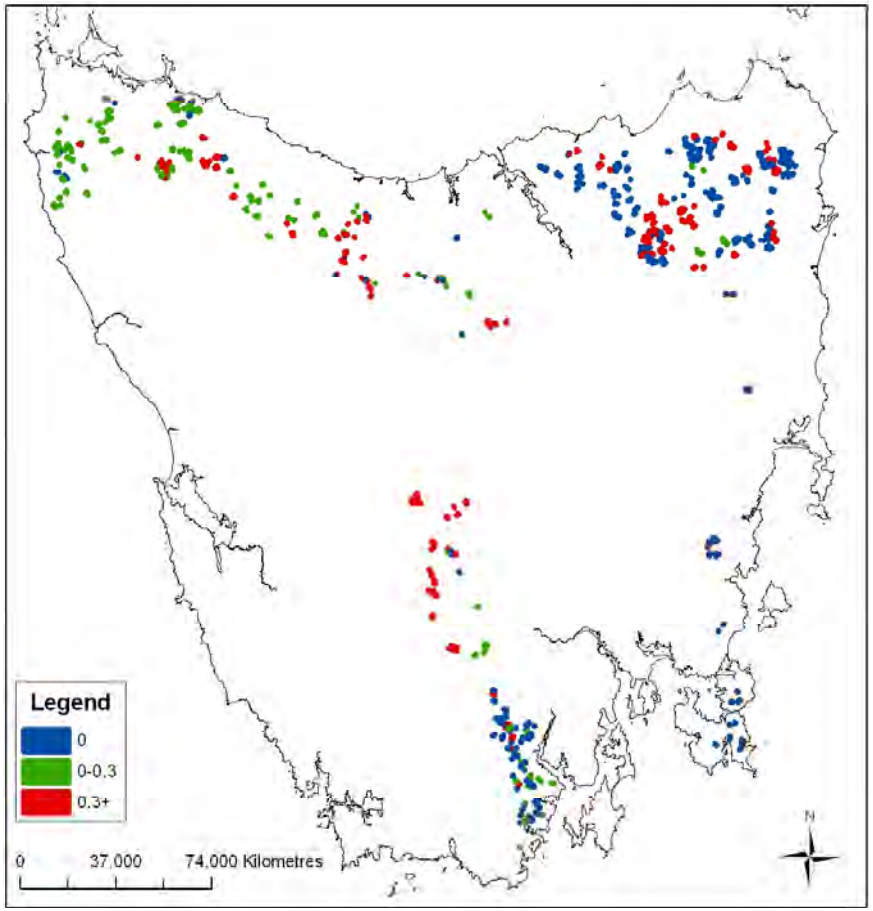


Figure 13: *P. bimaculata* beetle populations for the 2009/2010 season

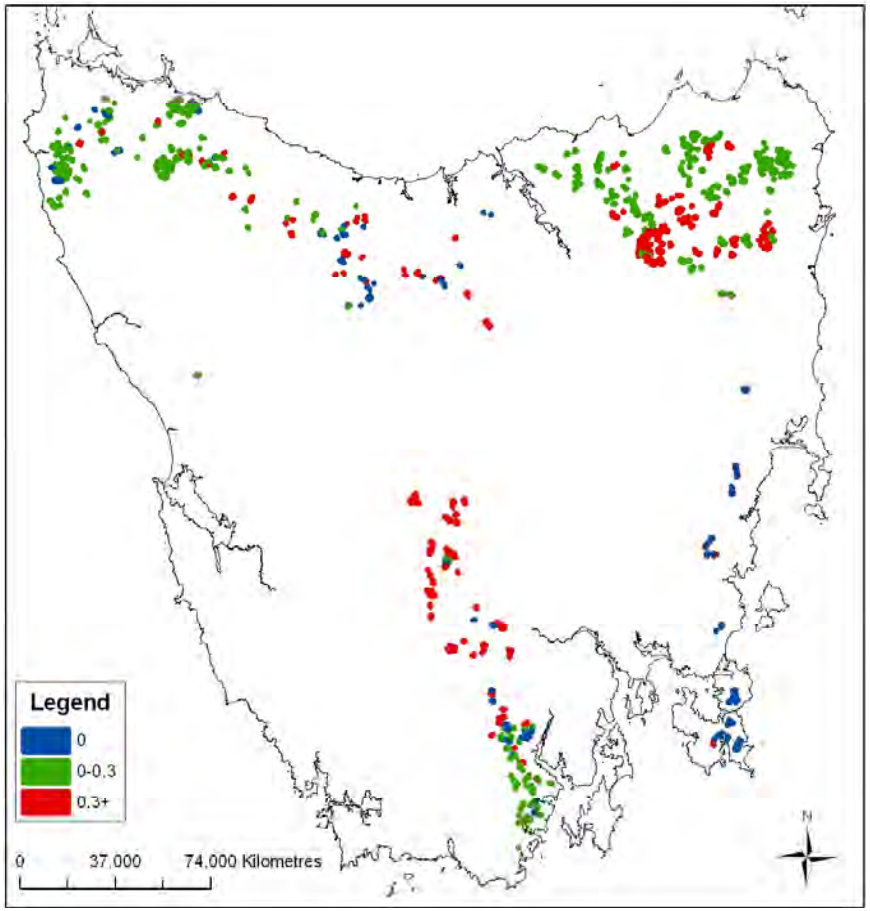


Figure 14: *P. bimaculata* beetle populations for the 2010/2011 season

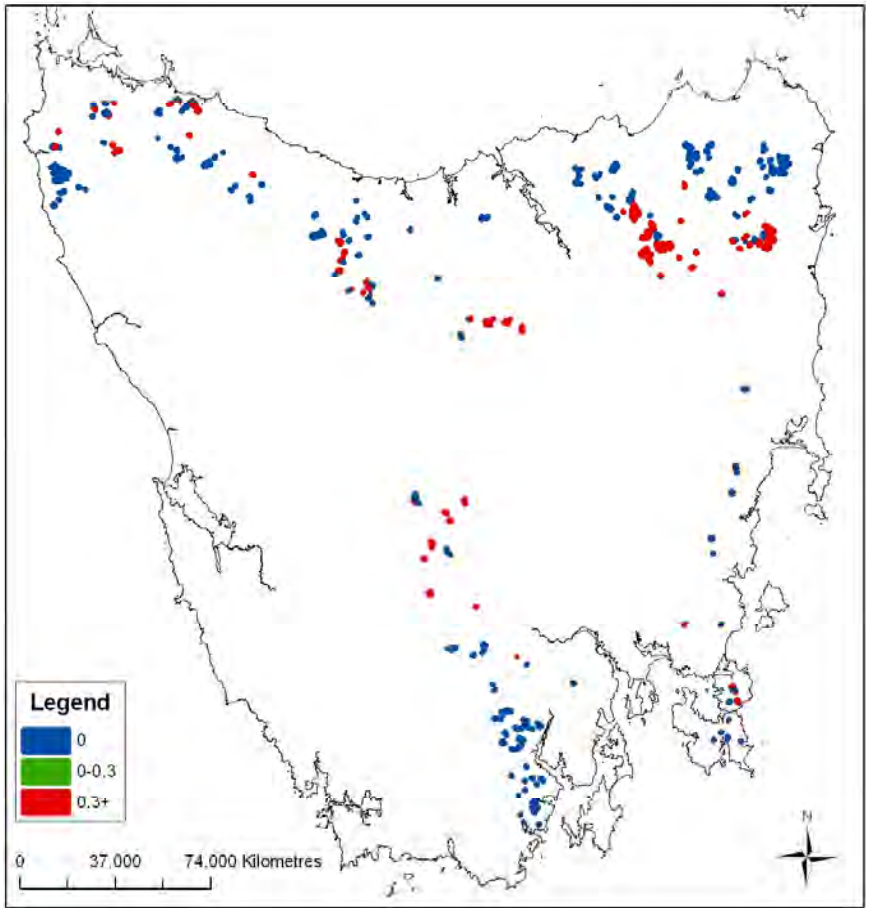


Figure 10: *P. bimaculata* beetle populations for the 2005/2006 season

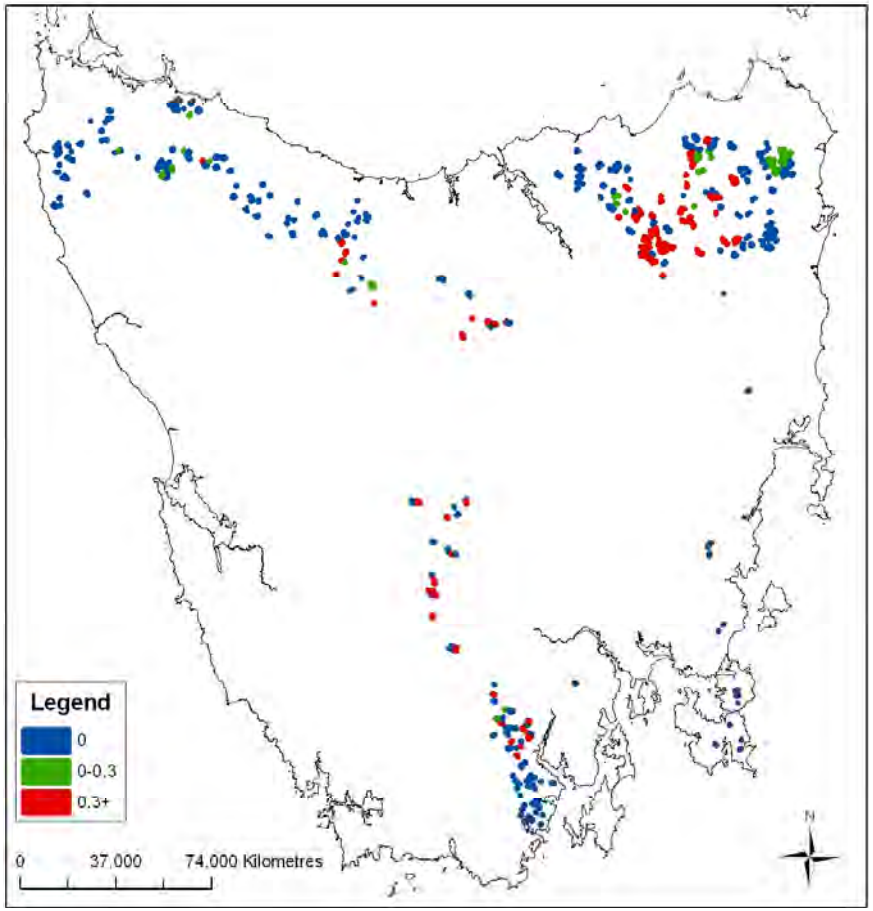


Figure 11: *P. bimaculata* beetle populations for the 2007/2008 season

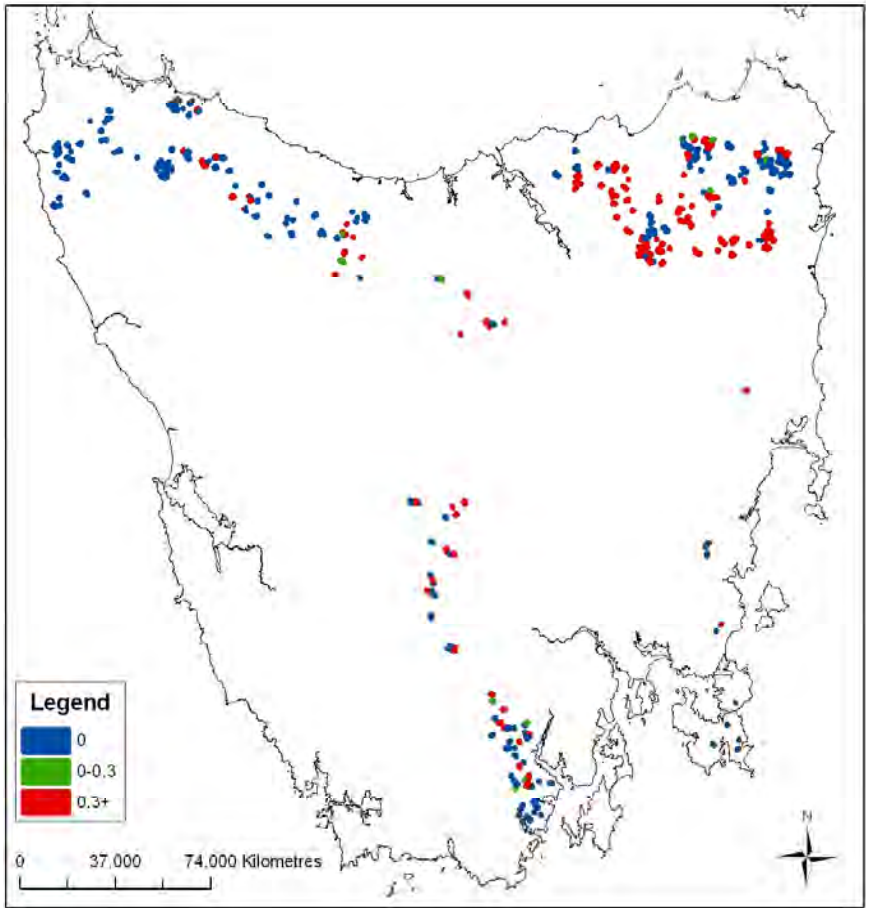


Figure 12: *P. bimaculata* beetle populations for the 2008/2009 season

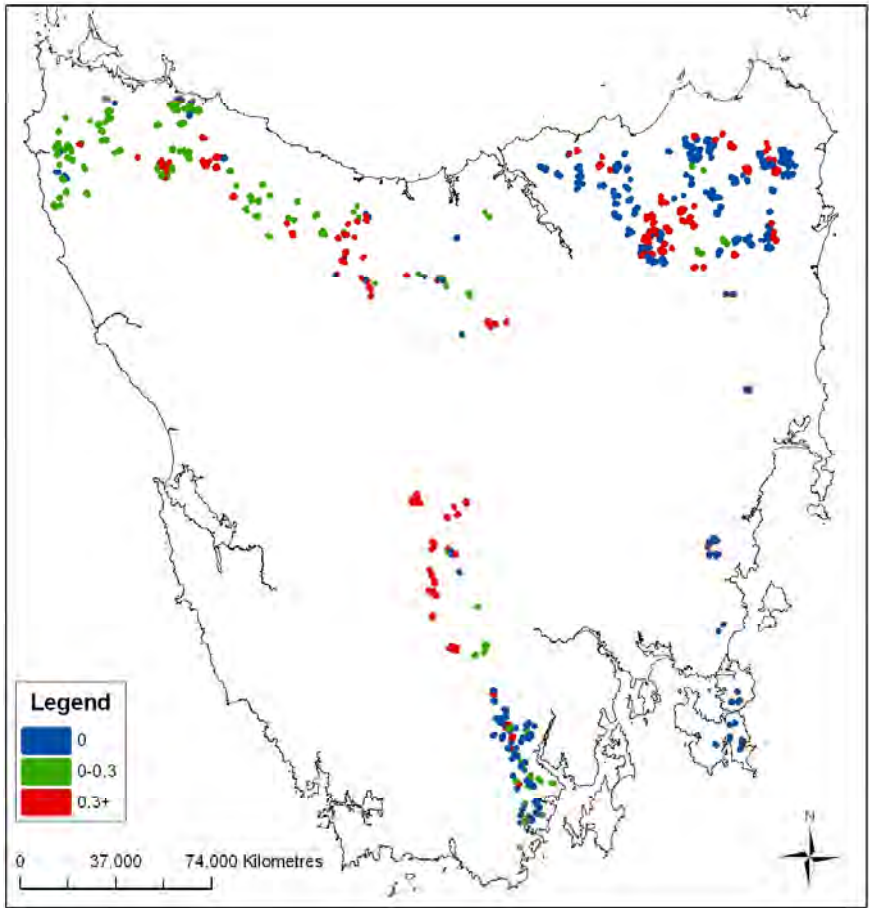


Figure 13: *P. bimaculata* beetle populations for the 2009/2010 season

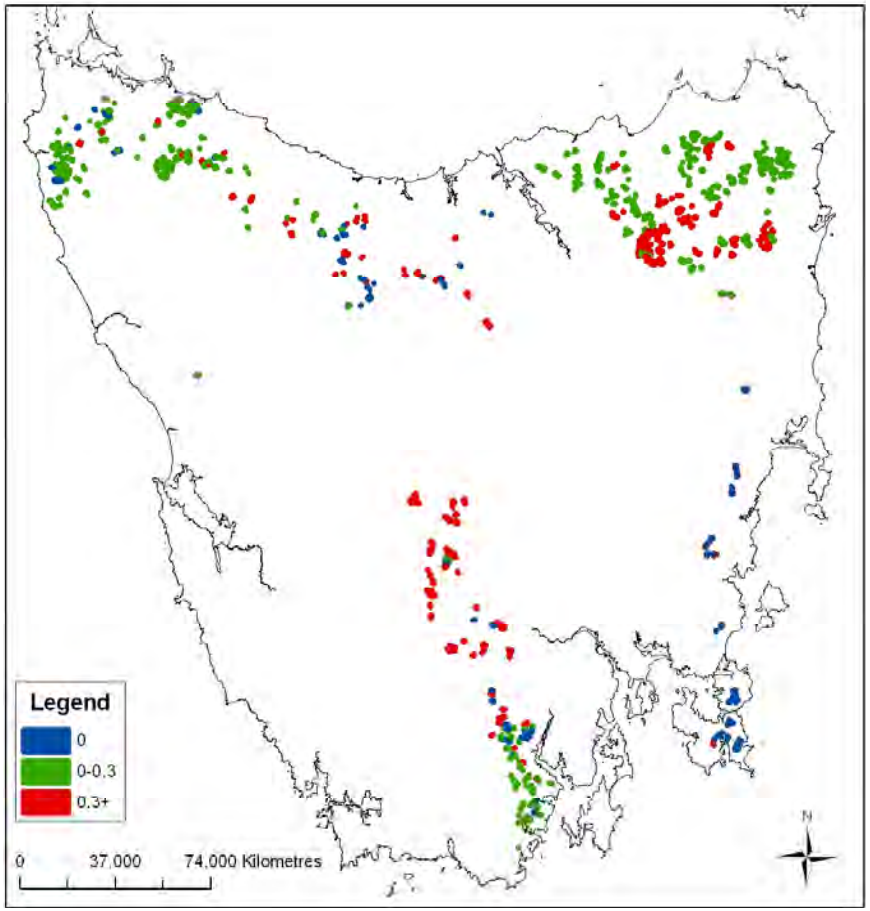


Figure 14: *P. bimaculata* beetle populations for the 2010/2011 season

3.3 Random forests analysis

3.3.1 Error matrix results

Error matrices were created and validated with random forests using a variety of district and season combinations for the four different climatic variables (Table 9). For these analyses OLPS rate was set at either >0.3 or <0.3. The overall error rates for each model were obtained (Table 9), along with the probability of a false negative (Table 10). The results show that the models with the lowest overall error rates were obtained when both 30 year averages plus actual summer rainfall and mean maximum temperature were included. Using the mean summer temperature and summer rainfall in the years of sampling generated the second-most accurate model. Inclusion of the 30-year mean for all climate variables ranked third in performance, while inclusion of the thirty-year mean for summer rainfall and summer mean maximum temperature generated the models with highest error rates.

Models based on data from Bass were less accurate than when data from all districts were included, which was in turn were generally less accurate than when all districts excluding Bass were modelled. When Bass is excluded from the model, little if any improvement was gained by analysis of individual years compared to all years. Also when a model is created using data from a particular year and validated with a different year, the models for all the districts and also Bass only are less accurate, while for all districts including Bass the model error rate shows little change.

In conclusion, the most accurate model developed pertained to all districts excluding Bass with all climate variables, including both 30 year averages plus actual summer rainfall and mean maximum temperature. However, error only decreased by 0.02 between the model based on 30 year climate averages and this model, with the former not including specific annual data and hence useful as a predictive model.

The model for all districts excluding Bass had a 10% rate of false negatives (Table 10). This indicates that one in ten results will be predicted to be below threshold, but would be instead over.

Table 9: Error rates for all models for 1) 30 year average plus actual summer rainfall and maximum temperature. 2) 30 year average for summer rainfall and summer maximum temperature only 3) actual summer temperature and rainfall in year of sampling. 4) 30 year mean for all climate variables

	Model training data	**all years (2/3rds)**	**2005/2006 (2/3rds)**	**2007/2008 (2/3rds)**	**2008/2009 (2/3rds)**	**2009/2010 (2/3rds)**
	Model validation data	all years (1/3rd)	**2005/2006 (1/3rd)**	**2007/2008 (1/3rd)**	**2008/2009 (1/3rd)**	**2009/2010 (1/3rd)**
1)	**all districts**	0.26	0.23	0.21	0.24	0.26
	Bass	0.32	0.08	0.2	0.29	0.23
	ex_Bass	0.2	0.17	0.22	0.23	0.21
2)	**all districts**	0.27	0.24	0.23	0.27	0.27
	Bass	0.34	0.13	0.2	0.39	0.25
	ex_Bass	0.2	0.2	0.18	0.23	0.23
3)	**all districts**	0.24	0.2	0.2	0.3	0.25
	Bass	0.29	0.1	0.2	0.39	0.26
	ex_Bass	0.19	0.2	0.17	0.24	0.22
4)	**all districts**	0.24	0.2	0.2	0.22	0.24
	Bass	0.26	0.08	0.25	0.25	0.25
	ex_Bass	0.18	0.2	0.19	0.23	0.22

Table 9 cont.: Error rates for all models for 1) 30 year average plus actual summer rainfall and maximum temperature. 2) 30 year average for summer rainfall and summer maximum temperature only 3) actual summer temperature and rainfall in year of sampling. 4) 30 year mean for all climate variables

	Model training data	**07/08, 08/09, 09/10**	**05/06, 08/09, 09/10**	**05/06, 07/08, 09/10**	**05/06, 07/08, 08/09**
	Model validation data	**2005/2006**	**2007/2008**	**2008/2009**	**2009/2010**
1)	**all districts**	0.28	0.27	0.32	0.38
2)	**all districts**	0.27	0.28	0.34	0.38
3)	**all districts**	0.3	0.24	0.36	0.31
4)	**all districts**	0.3	0.25	0.36	0.31

Table 10: Percentage of false negatives (predicted below threshold, but actually above) for 1) 30 year average plus actual summer rainfall and maximum temperature. 2) 30 year average for summer rainfall and summer maximum temperature only 3) actual summer temperature and rainfall in year of sampling. 4) 30 year mean for all climate variables.

	Model training data	**all years (2/3rds)**	**2005/2006 (2/3rds)**	**2007/2008 (2/3rds)**	**2008/2009 (2/3rds)**	**2009/2010 (2/3rds)**
	Model validation data	all years (1/3rd)	**2005/2006 (1/3rd)**	**2007/2008 (1/3rd)**	**2008/2009 (1/3rd)**	**2009/2010 (1/3rd)**
1)	**all districts**	16%	22%	16%	19%	23%
	Bass	16%	4%	12%	3%	19%
	ex_Bass	10%	17%	12%	18%	18%
2)	**all districts**	17%	23%	18%	21%	24%
	Bass	18%	4%	15%	7%	21%

	ex_Bass	10%	20%	14%	18%	21%
3)	**all districts**	16%	19%	17%	22%	22%
	Bass	15%	2%	12%	10%	21%
	ex_Bass	10%	20%	12%	18%	19%
4)	**all districts**	16%	19%	16%	19%	22%
	Bass	14%	4%	12%	3%	21%
	ex_Bass	9%	19%	12%	18%	20%

Table 10 cont.: Percentage of false negatives (predicted below threshold, but actually above) for 1) 30 year average plus actual summer rainfall and maximum temperature. 2) 30 year average for summer rainfall and summer maximum temperature only 3) actual summer temperature and rainfall in year of sampling. 4) 30 year mean for all climate variables

	Model training data	**07/08, 08/09, 09/10**	**05/06, 08/09, 09/10**	**05/06, 07/08, 09/10**	**05/06, 07/08, 08/09**
	Model validation data	**2005/2006**	**2007/2008**	**2008/2009**	**2009/2010**
1)	**all districts**	16%	10%	22%	14%
2)	**all districts**	16%	11%	23%	13%
3)	**all districts**	18%	11%	26%	17%
4)	**all districts**	19%	11%	25%	16%

3.3.2 Predicted model and actual results

The previous section (3.3.1) determined that the model using the thirty-year climate averages for Bass was one of the most accurate models, with an overall error rate of 0.2 and a false negative of 10%. A score for the probability of the relative frequency of the data being a true negative, false negative, true positive, and false positive was obtained. When entered into GIS there appeared to be few spatial trends between probabilities (Figure 15).

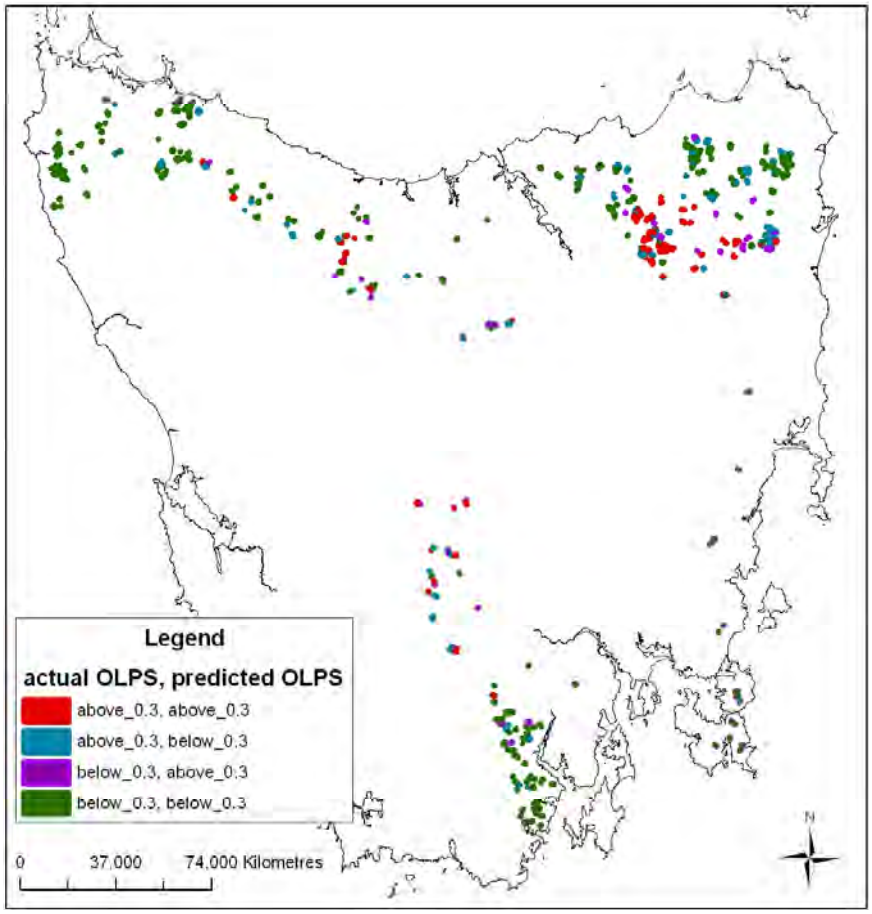
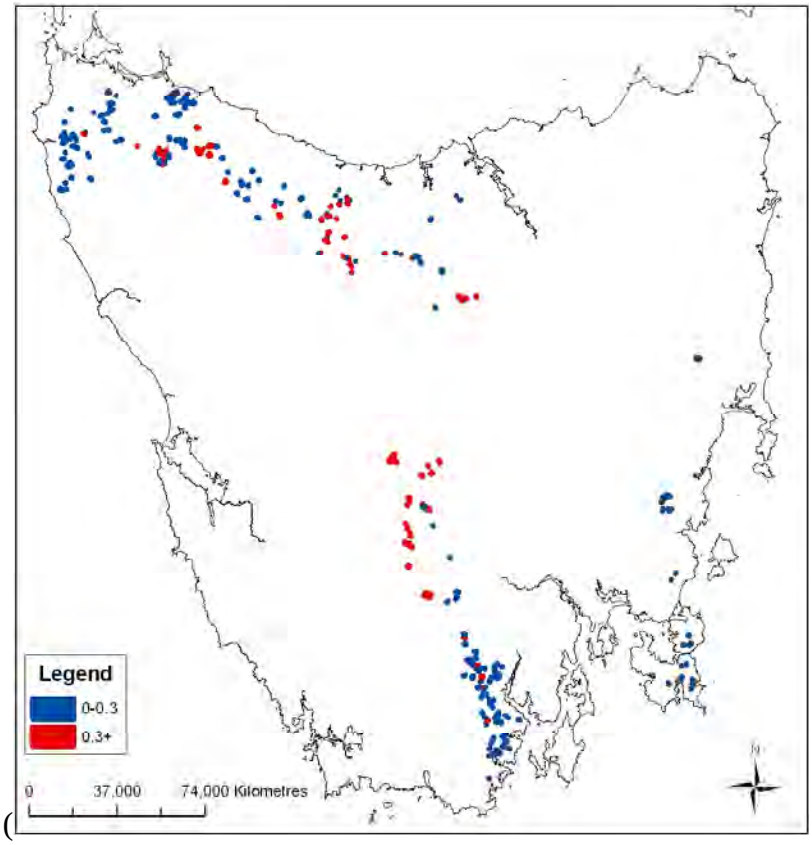


Figure 15: Relative frequency data showing true negatives, false negatives, true positives, and false positives (fix map)

A spatial layer of the predicted OLPS scores was then created to compare with the 2010/2011 data to see if predictions and observed results were consistent



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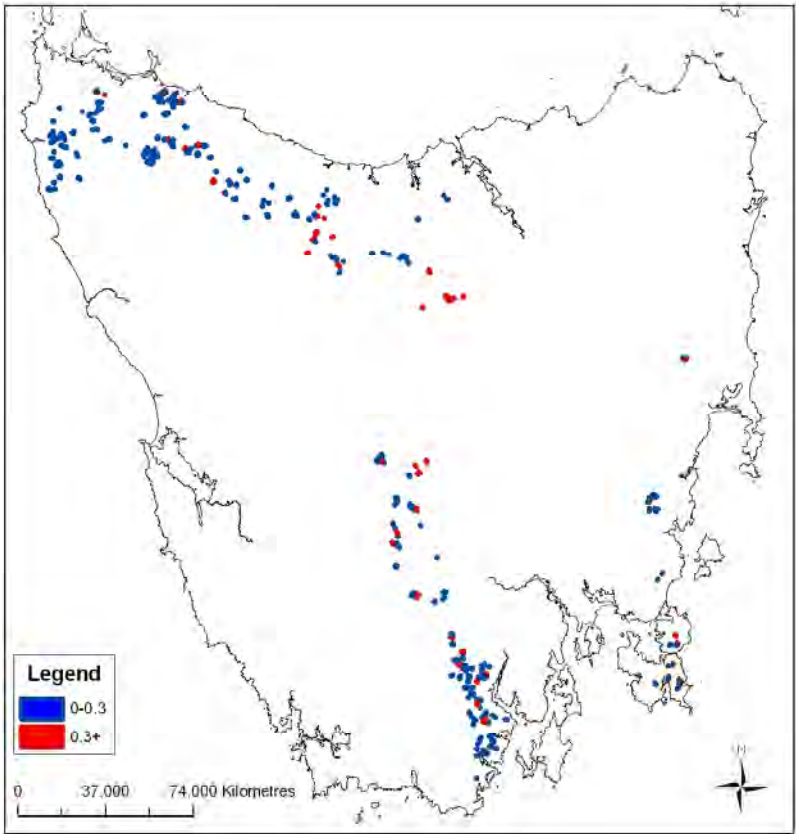
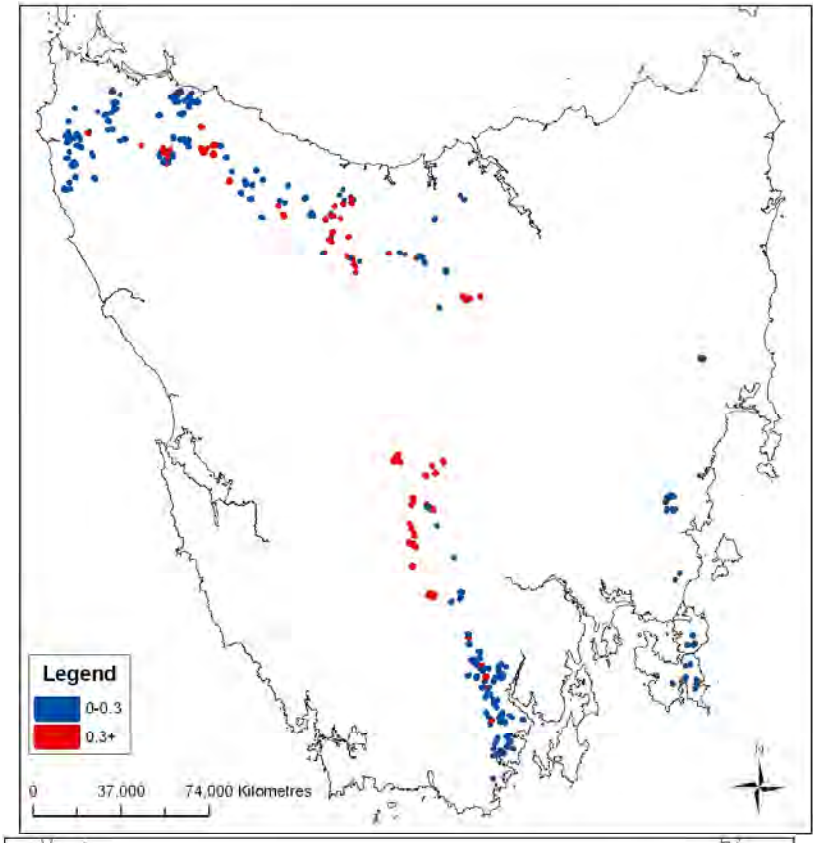


Figure 16). Although the actual and predicted results have some similarities, there is

a large number of coupes that were predicted to be under the OLPS threshold, but were in fact above.



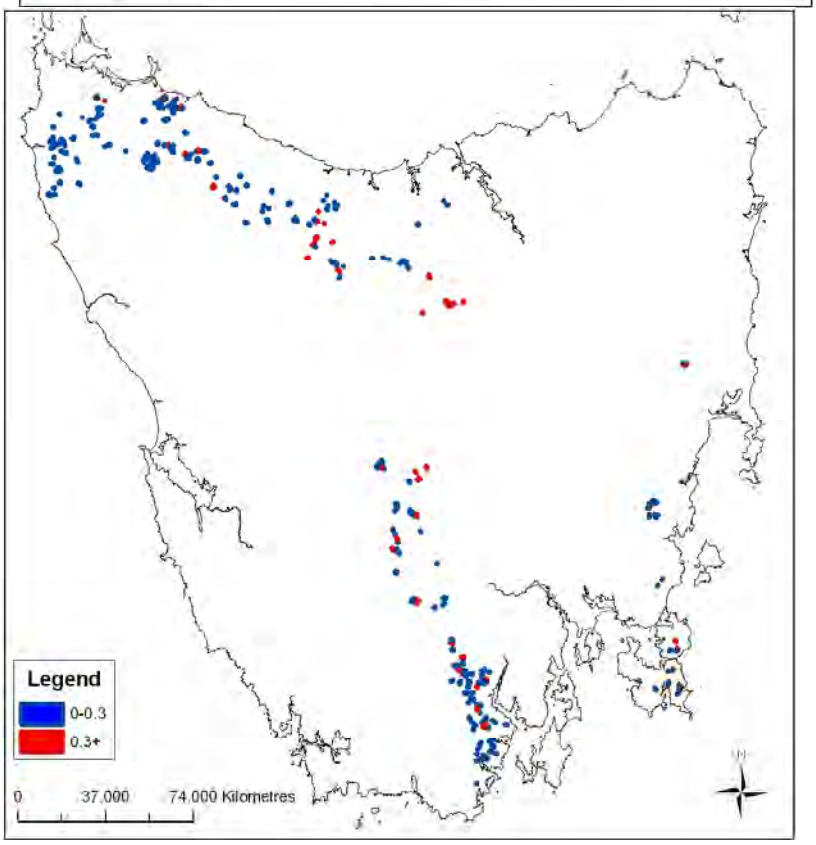


Figure 16: Comparing a) actual OLPS rates for the seasons from 2005/2006 to 2009/2010 with b) RF predictions from model based on rates for the same area from 2010/2011

3.3.3 Variable importance plots

Figure 17, which includes all 33 predictor covariates, provides an example of a variable importance plot (all districts across all years using 30 year climate data plus actual summer temperature and rainfall in year of sampling). A variable importance plot was created for each of the four combinations of climate variables for: all districts for all years and each individual season; Bass for all years; and all districts except Bass for all years. The ten top-ranking predictor variables for each random forest model is listed in appendix 3 and summarised in Table 11. When determining the mean variable ranking, any column which did not rank in the top 10 was given a value of 11, unless they were not assessed (e.g. surveyed year, or district), in which case that column was excluded.

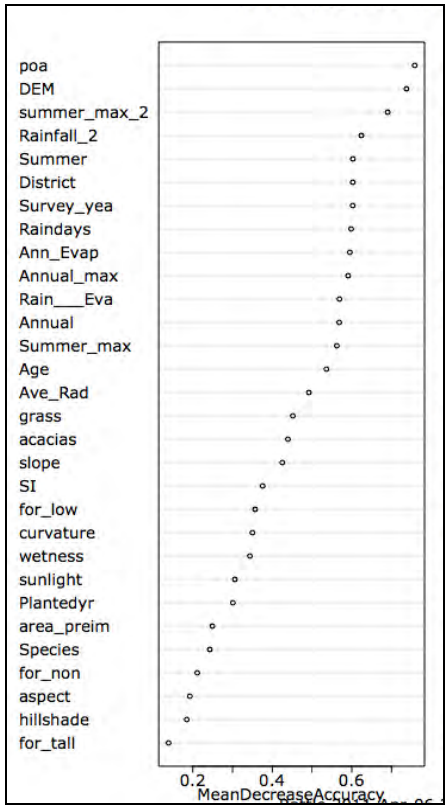


Figure 17: Variable importance plot for all districts across all years using 30 year climate data and actual summer temperature and rainfall in year of sampling.

Proximity to *Poa* was generally the most important predictor variable with regards to beetle distributions in all models tested closely followed by elevation

(DEM)(Table 11). Actual mean summer rainfall (rainfall_2) and district are also consistently important variables.

Table 11: Overall variable importance as derived from mean of ranks shown in Table 9

Variable	Overall Average
Poa	2.05
DEM	2.28
Rainfall_2	4.00
District	5.52
Summer_max_2	6.86
Summer_max	6.86
Raindays	7.00
summer	7.00
Annual_evap	7.43
survey_year	7.59
Annual_max	8.57
Ave_rad	8.86
For_low	9.09
rain___evap	9.14
Grass	9.38
Acacia	9.48
Age	9.62
Slope	9.76
Annual	9.86
Species	10.00
wetness	10.33
curvature	10.43
sunlight	10.57
hillshade	10.57
Planted year	10.67
Area_perim	10.72
For_tall	10.86

The parameters that contribute least to optimal models and never occur in the top ranked ten predictors are area of coupe, perimeter of coupe, aspect, distance to non-eucalypt forest, distance to non-forested area, and site index (

Table 12).

Table 12: Variables not ranked in the top 10 for models that include four different combinations of climate variables. 1) 30 year average plus actual summer rainfall and maximum temperature. 2) 30 year average for summer rainfall and summer maximum temperature o

	1)	2)	3)	4)
Area_ha	x	x	x	x
aspect	x	x	x	x
For_less	x	x	x	x
For_non	x	x	x	x
perimeter	x	x	x	x
SI	x	x	x	x
Acacia	x		x	
Area_perim	x		x	
curvature	x		x	
For_tall	x		x	
Planted year	x		x	
sunlight	x		x	
wetness	x		x	
Rainfall_2		**N/A**	**N/A**	
Summer_max_2		**N/A**	**N/A**	
Ave_rad		**N/A**		**N/A**
Annual		**N/A**		**N/A**
Annual_evap		**N/A**		**N/A**
Annual_max		**N/A**		**N/A**
rain___evap		**N/A**		**N/A**
Raindays		**N/A**		**N/A**
Grass	x			
Slope	x			
Summer (rainfall)				**x**
Sumer_max				**x**

Mean variable importance was determined for Bass, and for all other districts excluding Bass (Table 13). As in the previous table, when assessing the mean variable ranking, any column with rank outside the top 10 was given a value of 11 unless they were N/A (e.g. annual mean summer rainfall, district etc.), in which case that column was excluded. In the district of Bass, survey year is generally the most important factor, followed by proximity to *Poa* grasslands, annual mean summer rainfall (rainfall_2) and elevation (DEM). Proximity to *Poa* grasslands and elevation are still important variables when Bass is excluded from the results, however, survey year and annual mean summer rainfall both become unimportant. Age of a plantation is also far more important when Bass is excluded. District is an important variable in all districts except Bass, but could not be included in the Bass analyses because it was only one district.

Table 13: Results for average variable importance for Bass, and for when Bass is excluded (an empty space means variable importance ≥ 10.

Variable	Mean variable importance for Bass	Mean variable importance when Bass is excluded
survey_year	1.5	
Poa	2.5	1.5
Rainfall_2	2.5	9
DEM	3.25	1.5
Ave_rad	6.5	
rain___evap	6.5	8
Annual_evap	7	6
Summer_max	7.75	6.5
Summer	8	
Summer_max_2	8	
Annual	8.5	5.3
Raindays	8.5	8
Grass	8.75	
Annual_max	9.5	6
For_low	9.5	
curvature	9.75	
Species	9.75	
District	N/A	3
Age		5.3
Acacia		9
Planted year		9.5
Area_perim		9.8

3.3.4 Partial dependency plots

For variables that appeared to have the greatest influence on *P. bimaculata* distribution a partial dependency plot was created for a) all districts, b) all districts excluding Bass, and c) Bass only. These variables included elevation, proximity to *Poa*, summer mean rainfall for individual seasons, age of plantation and district.

For all three district combinations, a slight decrease in beetle populations occurred at the lowest altitudes followed by a large increase with increasing elevation, however, the slope for the three combinations varied. The 'all districts' plot showed a relatively steep increase in beetle populations with altitude, converging at about 650 m, whereas the 'districts excluding Bass' plot had two plateaus, the first between approximately 250 and 550 m, and the second at around 600 m. The partial dependency plot for Bass showed a rapid increase between 300 and 400 m, where it reached an asymptote.

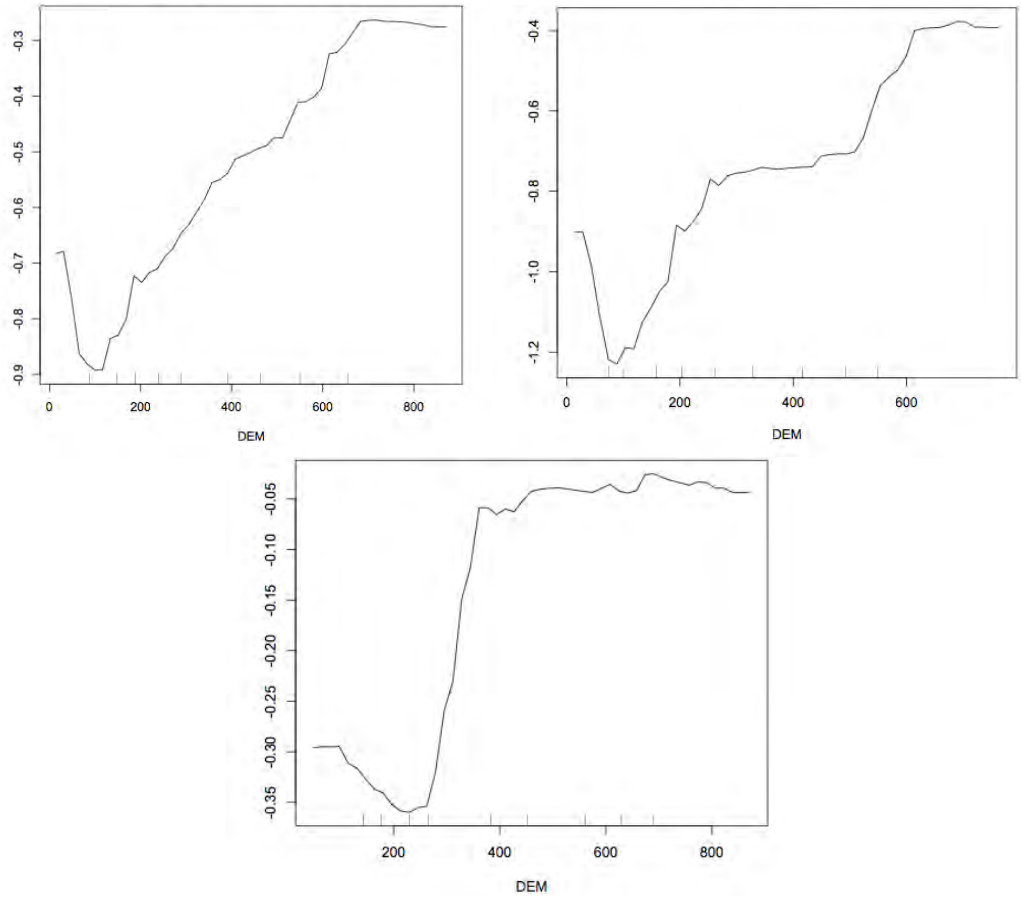


Figure 18: Partial dependency plot of elevation for a) all districts, b) all districts excluding Bass and c) Bass only

Paropsisterna bimaculata populations show a marked decrease at 10 km distance from *Poa* grasslands for all three combinations of districts (Figure 19). As approximately 54% of the data is within 10 km distance from *Poa* grasslands, and this sharp decline occurs in both Bass and when Bass is excluded, this sharp decline is unlikely to be an anomaly in the data.

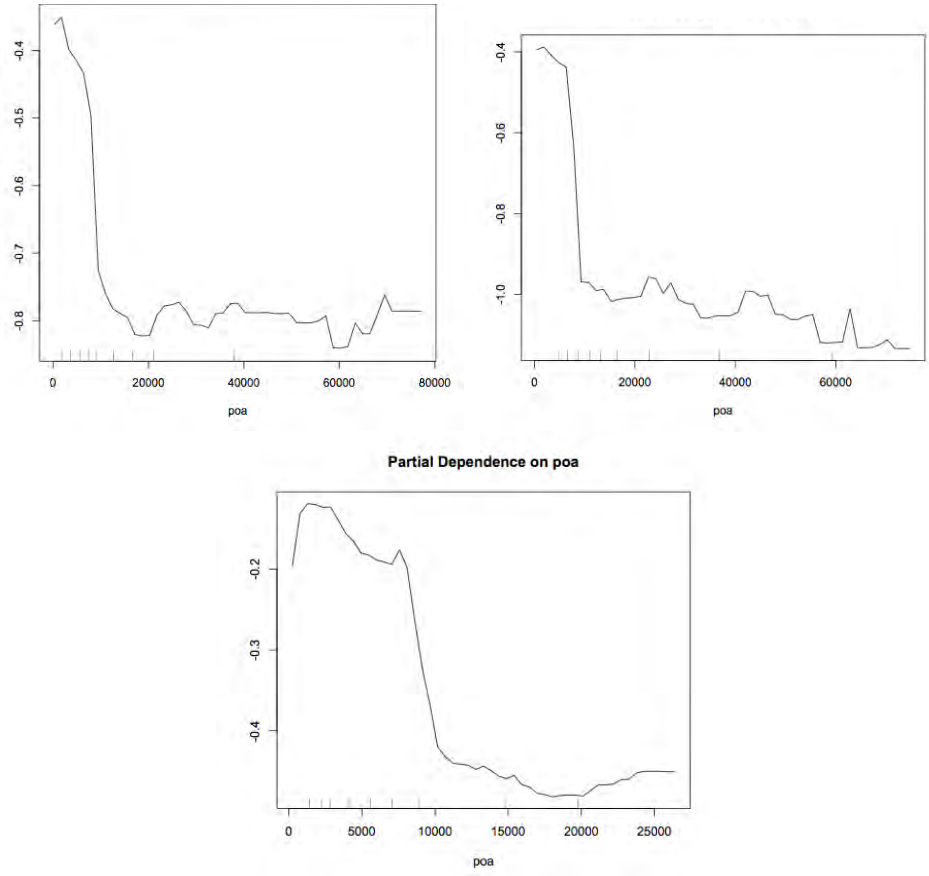


Figure 19: Partial dependency plot of Poa for a) all districts, b) all districts excluding Bass and c) Bass only

Mean summer rainfall using data from the years of beetle observation showed significant difference between district combinations (Figure 20). All combinations show a drop in beetle population numbers towards 100-200 mm, however after this point the graph for all districts showed beetle numbers remaining low, except for two peaks at about 400 mm and 600 mm. ; Districts excluding Bass showed a steady gradual increase after this point, and Bass showed an increase, before dropping in

value at 450 mm. These results compare to the prediction that numbers should increase with rainfall, which is associated with increased tree productivity.

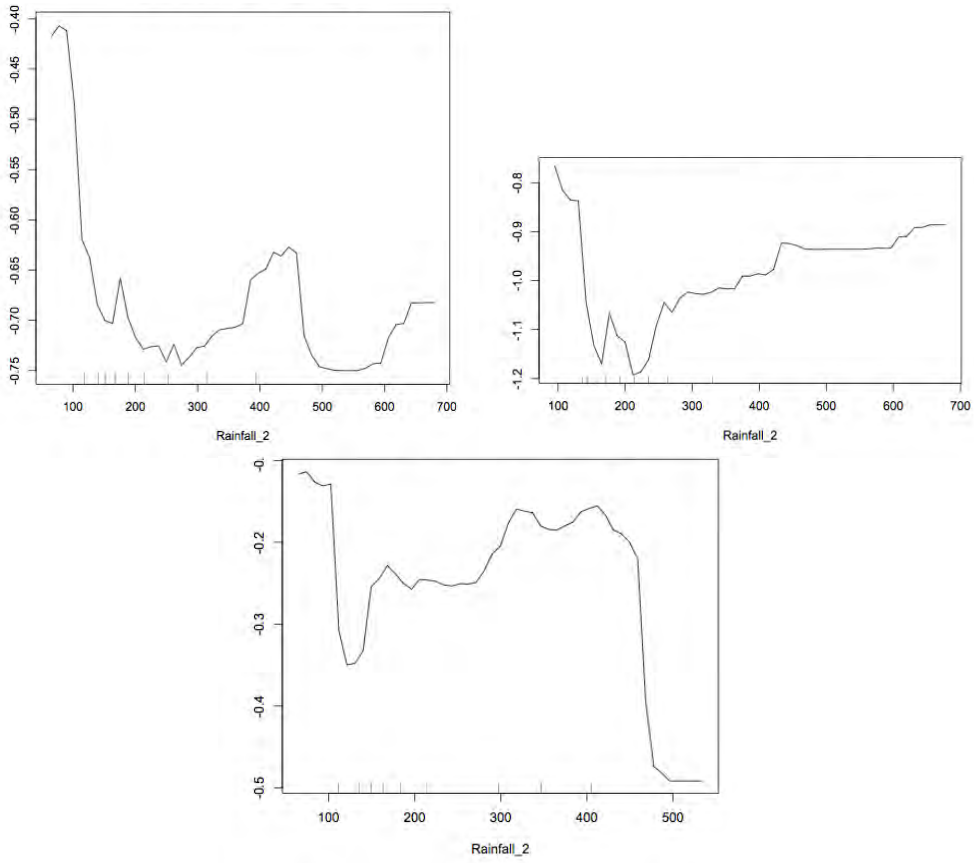


Figure 20: Partial dependency plot for actual mean maximum summer rainfall for a) all districts, b) all districts excluding Bass and c) Bass only

Age of eucalypt plantations for all districts, and all districts except Bass, indicated stronger dependency with beetle populations up to approximately 8 years (Figure 21). However when Bass was analysed separately, a rapid increase was evident between 2 and 4 years, followed by a decrease from 5 to 7 years, and then stabilisation (Figure 21).

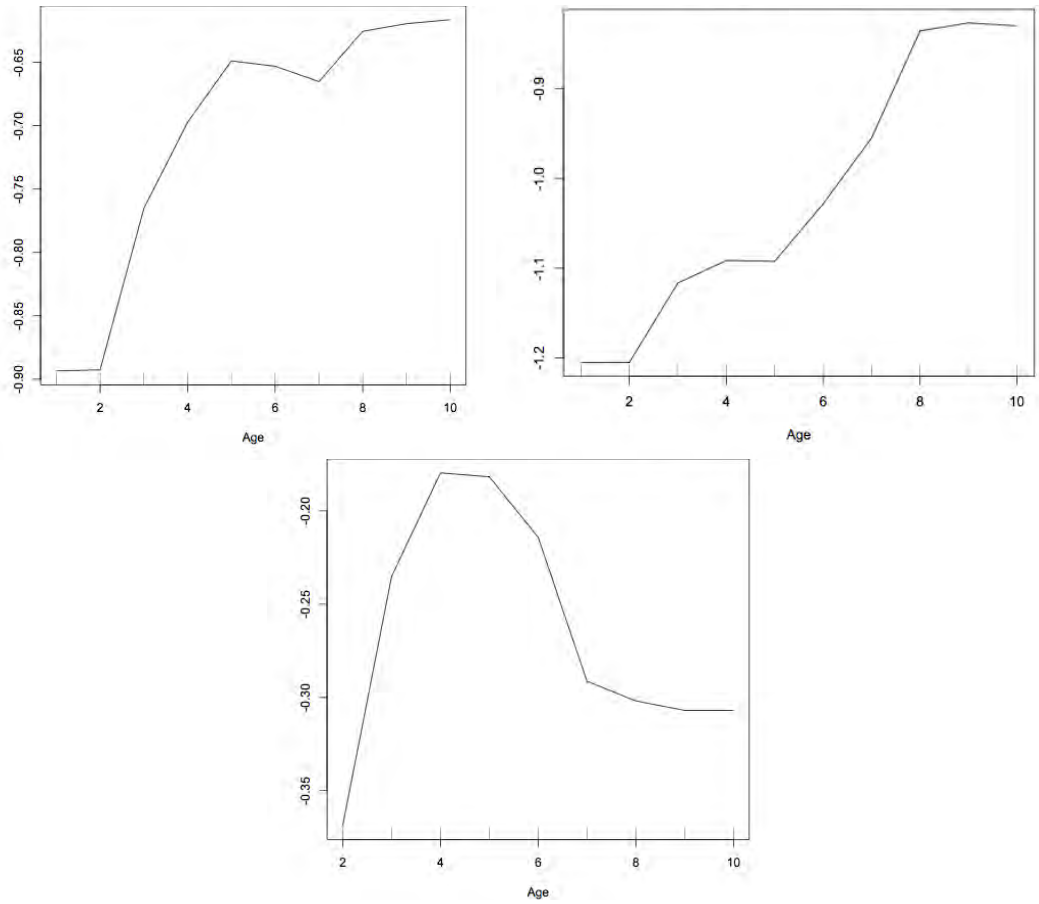


Figure 21: Partial dependence plot on age for a) all districts, b) all districts excluding Bass and c) Bass only

Figure 22 shows that effects of district on beetle numbers are highest in Bass, Derwent and Mersey when compared with Huon and Murchison.

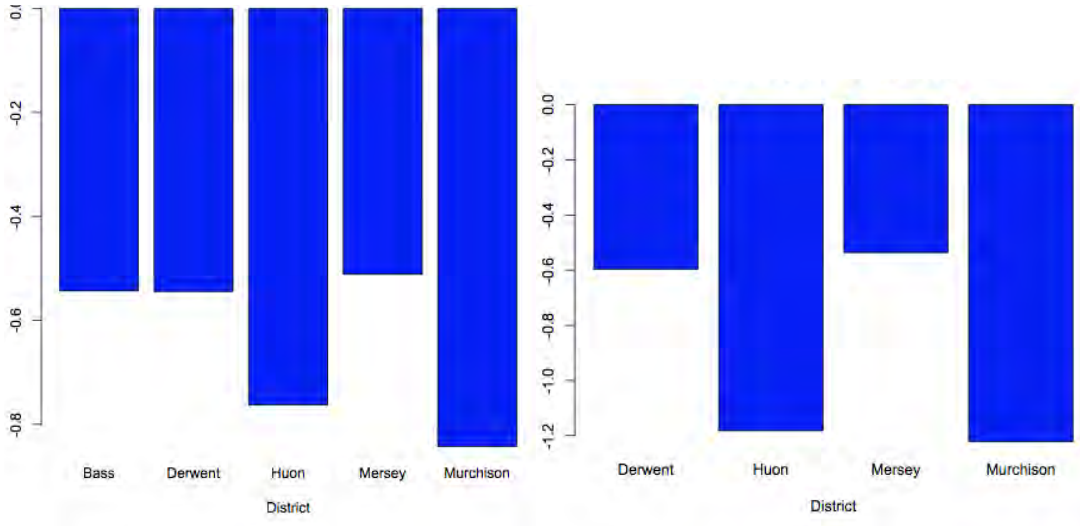


Figure 22: Partial dependence plot of district for a) all districts, and b) all districts excluding Bass

3.4 DEM and Poa

The results for districts excluding Bass described above (section 3.6) indicated that a distance of less than 10 km to Poa grasslands and an elevation of over 550 m were most strongly related to elevated populations of *P. bimaculata*. Two layer files were created for areas of Tasmania that were less than 10 km from Poa grasslands (Figure 23) and above 550 m altitude (Figure 24). These were combined to show areas with low likelihoods of beetle infestation (i.e. distance > 10 km from Poa, and elevation < 550 m)(

Figure 25), and areas of high likelihood of beetle infestation (i.e. distance > 10 km from Poa, and elevation < 550 m)(

Figure 26).

Out of 3126 coupes, 630 coupes intersect this area (are high risk cases) and 1511 are low risk cases. The rest are moderate cases being either close to Poa grasslands but at lower elevations, or at higher elevations, but further away from Poa grasslands.

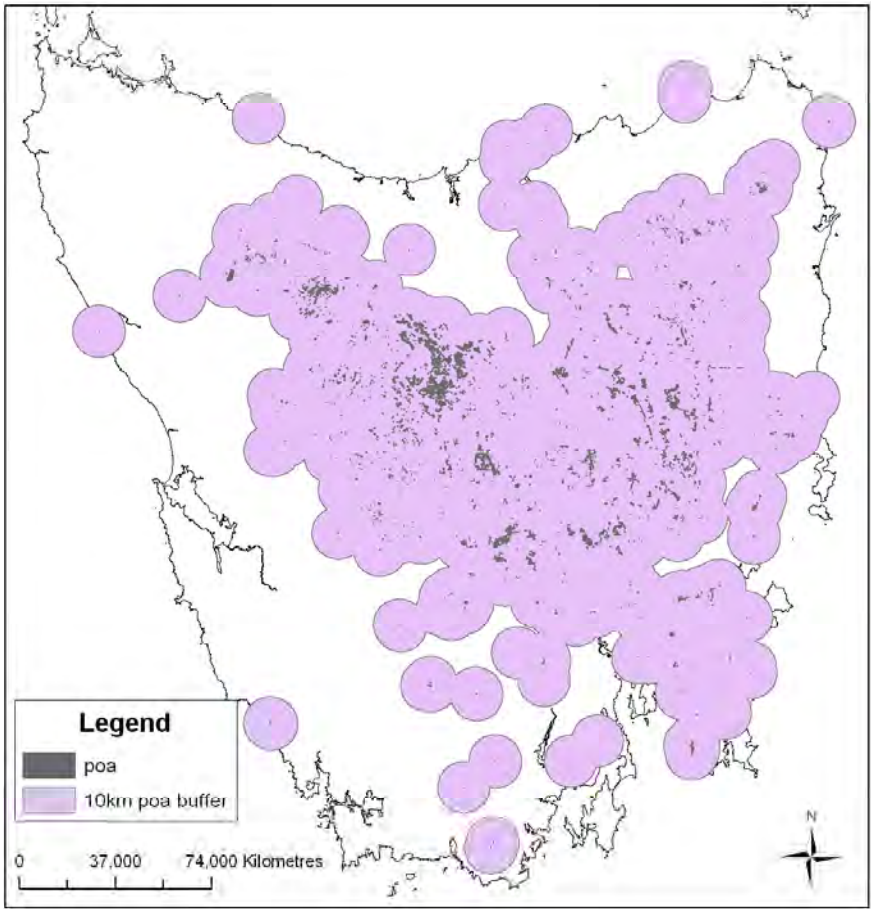


Figure 23: Distance from Poa less than 10 km

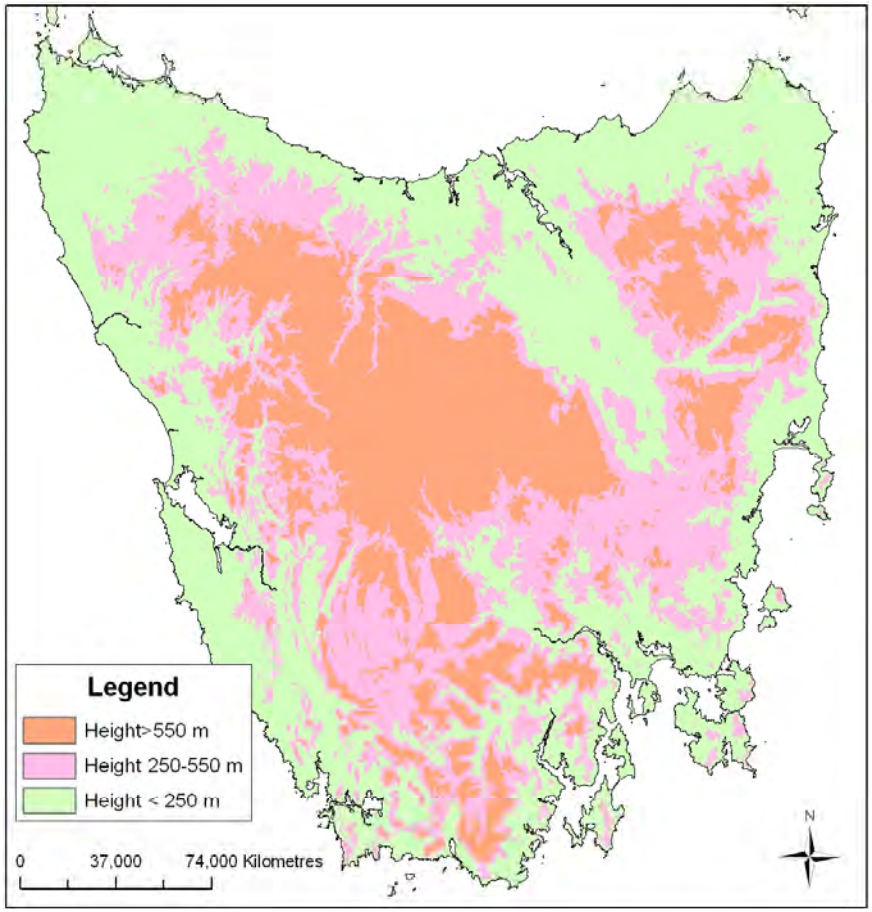


Figure 24: Elevation

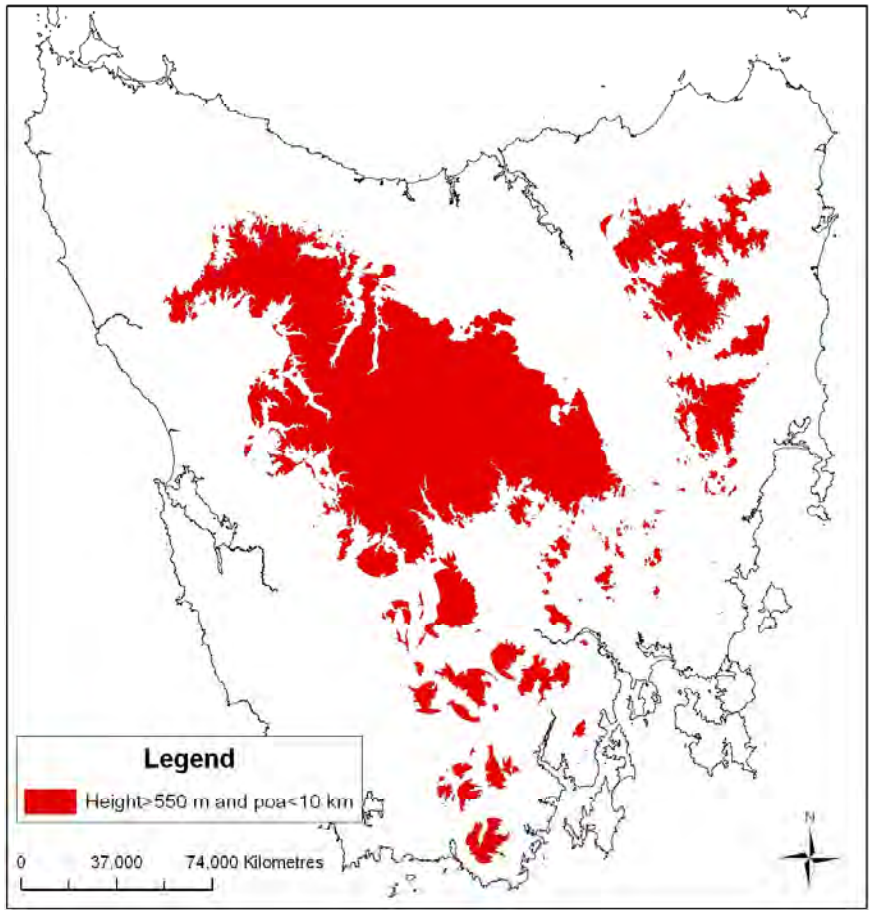


Figure 25: Distance from Poa < 10 km and elevation > 550 m where likelihood of beetle populations is high

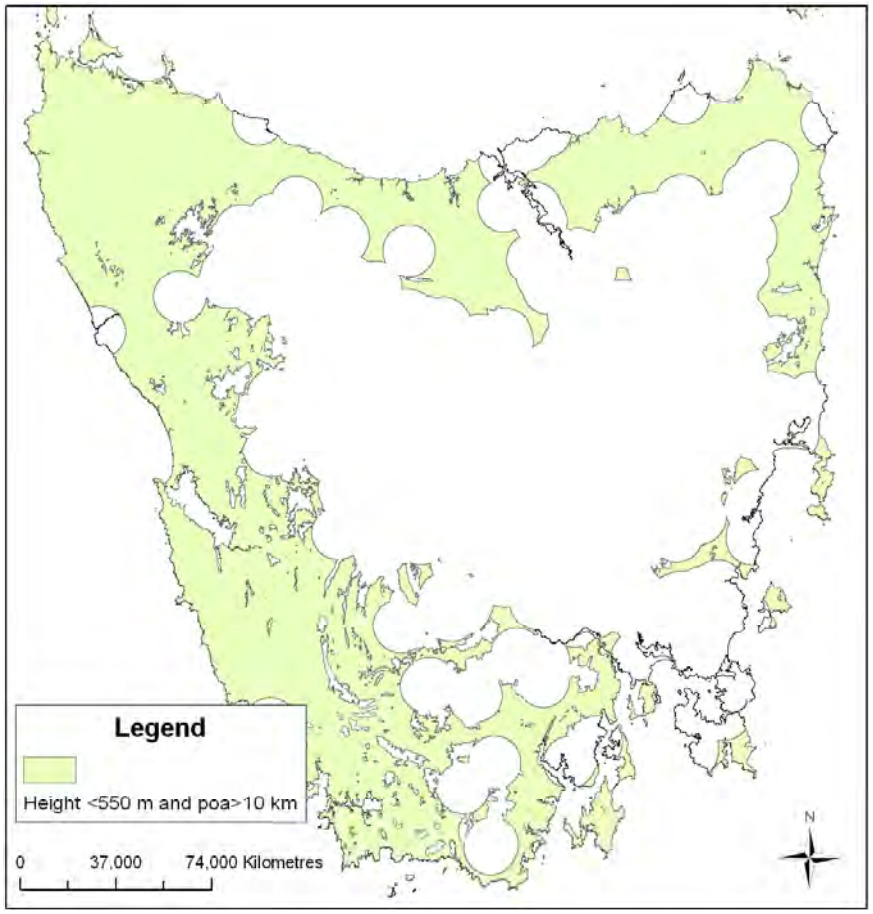


Figure 26: Distance from *Poa* > 10 km and elevation < 550 m, where beetle likelihood is low

Chapter 4 Discussion

4.1 *Variable importance*

Of the seven *a priori* hypothesis that were made at the start of this study, only three were proven correct. *Paropsisterna bimaculata* numbers were most frequently correlated with proximity to *Poa* grasslands and high elevations, with numbers of *P. bimaculata* rapidly decreasing at approximately 10 km distance from *Poa* grasslands, but increasing as elevation increased. These results are important for management of *P. bimaculata* as few studies have been conducted on these variables.

The results regarding the hypothesis for importance of overwintering sites was complex because although the analysis of proximity to broadscale grasslands showed little correlation with *P. bimaculata* populations, proximity to *Poa* grasslands was highly correlated. This suggests that *Poa* tussocks are potentially an overwintering site for *P. bimaculata* and of greater importance than *Gahnia grandis.* As TasVEG only provides information for dominant vegetation classes, there were no data available on non-dominant vegetation including *G. grandis.* However, some dominant vegetation types such as *Eucalyptus viminalis* grassy forest and woodland may have a dense understorey of *Poa* grasslands, which is impossible to determine from TasVEG vegetation layer given its lack of detail in vegetation community structure. This means that it is possible that further studies on *P. bimaculata* and *Poa* species may show an even greater correlation between the two, as this study under - represents the full distribution of *Poa*. Similarly, the relationship with *G. grandis* remains to be resolved given the frequency that *G. grandis* occurs in disturbed ground including roadside verges, at a scale too small for available habitat maps.

District appears to also be an important variable (Hypothesis 5). Bass, Mersey and Derwent show a greater correlation with increased beetle populations than Huon and Murchison. When analysed separately from the other districts, Bass showed

markedly different variables of importance. Survey year and mean summer rainfall for individual years were of high importance for Bass, but being less significant for the other districts. Age appeared to be significant for the other four districts when analysed together, but not for Bass.

Age was also ascertained to be a strong correlate with beetle populations in the districts excluding Bass, but not in the overall data or in Bass, thereby partially confirming hypothesis five. The models excluding Bass, and the overall models, both showed that beetle populations increased with age before reaching an asymptote at around 8 years, which supports results from previous studies by Greaves (1966) and De Little (1983, 2008).

In Bass there was a sharp decrease in beetle populations with rainfall to 200 mm that did not support the hypothesis of increasing beetle numbers with rainfall and vegetation productivity (Clarke et al. 1997; Candy 1999), but from 200 mm beetle populations increased as predicted. However, the majority of other measures of productivity such as site index and aspect, as well as other climate factors such as incoming solar radiation, were found to have low correlations with beetle outbreaks.

The hypothesis that high populations of *P. bimaculata* occur in favourable weather conditions, such as sunny days or high temperatures (Greaves, 1966; Leon, 1989), is not supported by this study because solar radiation and temperature contribute little towards the accuracy of the model. As climate factors are interpolated between weather stations and thus are not accurate to each specific location, further study of climate at specific sites, especially for rainfall, would likely lead to stronger modeled relationships and a greater understanding of factors influencing *P. bimaculata* beetle populations.

Survey year was generally the most important factor in the district of Bass, however when Bass was excluded from the analysis survey year became unimportant. This indicates that in Bass *P. bimaculata* beetle populations fluctuate substantially from year to year due to untested variables, or low accuracy of tested variables. This makes it difficult to accurately predict where *P. bimaculata*

populations will occur in Bass each year. Consequently, population models for Bass should be regarded as less accurate than for other districts, where survey year was the least informative metric in predicting *P. bimaculata* populations.

Area and perimeter showed very little relationship with *P. bimaculata* populations, which does not support hypothesis four and indicates that edge effects related to the size of a coupe and the size of its perimeter are relatively unimportant. Although beetle numbers have been found in other studies to be highest along plantation edges (Clarke *et al*. 1998), the outcome found here is not consistent given that many coupes are adjacent to other coupes, so effectively have a larger area of forest than individual coupe size. Furthermore, roads and tracks run through most coupes, which effectively subdivide the coupes into smaller areas. Species of *Eucalyptus* was also found to have little impact on the model, which supports the results by De Little *et al.* (2008), but not Wardlaw *et al.* (2010).

Hypothesis six was not upheld as proximity to *Acacia dealbata* along with tall eucalypt forests, low eucalypt forests, non-eucalypt forests, and no forests, had little correlations with beetle populations. This low correlation with *Acacia dealbata* does not support Greaves (1966) that *Acacia dealbata* are important for predator species. However, once again *Acacia dealbata* is only a measure of dominant vegetation class and there may be other dominant vegetation types with *Acacia dealbata* present. The low importance of proximity to different vegetation types is unsurprising considering the amount of each vegetation type in close proximity to plantations was not assessed. If the study were to be re-conducted it would be of greater value to create a buffer around plantations and determine the percentage of each vegetation class within a distance of the coupes.

Defoliation damage from previous years is not assessed in this study as the same coupes for different seasons are considered to be different input values. Further studies looking at differences between coupes over time would probably bring greater accuracy to the model, however, it is not a simple study to conduct as some variables

such as plantation age change over time.

The random forests models that included only the district Bass had a higher error rate than those models that included all the districts or included all the districts except Bass. This confirms the hypothesis that Bass has a greater variability in beetle populations than other districts, which is potentially due to the greater variation in elevation (Wardlaw, pers. Comm. 2010). When using three seasons of data for all districts to create the model, and one season to validate it, the error rate is greater than using two-thirds of the four seasons to create the model and one-third to validate it. This indicates that a model that includes Bass would be relatively inaccurate due to the variability between seasons.

The most effective of the four different climate combinations used to create the random forests model was using 30 year mean (1961-1990) for all climate data plus summer rainfall and mean summer maximum temperature for the actual summer of beetle counts. The random forest technique is designed so that increasing the number of variables, even if they have low correlation with the predictor variable and high correlations with other variables, does not reduce the accuracy of the model. However, using the two variables, mean summer maximum temperature and mean summer rainfall for the individual years of beetle surveys was more accurate than using a higher number of variables, but for thirty year averages. Using thirty-year averages for mean summer rainfall and mean maximum summer temperature was the least effective model indicating that thirty-year averages for other climate variables have some importance to the predictive power of the model. Hence if other climate variables such as number of rain days, and annual evaporation were obtained for individual years, then the model would likely have a greater accuracy.

The model with the smallest error rate overall was the model for all districts excluding Bass with 30 year means (1961-1990) for all climate data plus summer rainfall and mean summer maximum temperature for the actual summer of beetle counts. However, the error only decreased by 0.02 between the model based on 30-year climate averages and this model. As it is not possible to obtain annual averages for future seasons, this indicates that climate averages would have only slightly greater error rates than actual data. This is probably also because climate data is

interpolated between weather stations, and a greater accuracy of climate data would produce more accurate models.

4.2 Annual beetle numbers

The percentage of coupes with an OLPS of 0 was found to decrease over time, and percentage of coupes with an OLPS of 0-0.3 increased over time, regardless of relatively stable trends between years in frequency of high beetle counts (OLPS >0.3) changed. This could be attributed to human error such as incorrect data entry, an increase in vigilance of first-stage monitoring, or a gradual increase of low beetle numbers across a larger distribution. Although Forestry Tasmania operatives confirmed that this result was possibly because of incorrect data entry for Murchison-West, the fact that high 0-0.3 levels remained consistent all over the state in the 2010/2011 season means this is unlikely (Jordan, 2011, pers. comm.).

Alternatively, through time the beetle is possibly becoming more widely distributed across all districts in low numbers, however, the particular combination of variables that facilitate beetle outbreaks at particular locations has remained stable. Another possibility is that people undertaking first stage monitoring are becoming more adept at spotting beetles and their offspring, and so more likely to continue with second stage monitoring. As large amounts of OLPS recordings that were for 0.01 or 0.02 in the 2009/2010 season (18% of total results) and even higher in the 2010/2011 season (26% of total results), this indicates that there is a strong likelihood that this is the case.

Temporal effects were not taken into account in the spatial analyses, which is a major gap in this study. Coupes that were measured in consecutive years were regarded as separate results, without comparing changes over time. As *P. bimaculata* consumes new-season foliage, and thereby limiting annual growth of plantations (Clarke *et al.* 1997), coupes with large beetle infestations one year are likely to have their growth stunted, and not be as attractive to beetles the following year. Further analysis of temporal variability of beetle populations would enable

forest managers to have a greater understanding of *P. bimaculata* and improve management practices.

4.3 Benefits and costs in using random forest model output to guide field surveys

The model for all districts excluding Bass using thirty-year climate averages had a 10% rate of false negatives, indicating that one in ten results will be predicted to be below threshold, when in fact it is over, and this would incur a predicted $119.95 loss per hectare if not sprayed.

For the current sampling regime, all forestry coupes are monitored, which in this case is 300, so the incurred cost of monitoring is 300x$10.2 per hectare. The number of results above 0.3 was 61 so the averted value for coupes minus the cost of spraying was 61x($189-$44.6) per hectare, and there is no incurred loss as all coupes were monitored so effectively sprayed. Therefore the predicted net profit obtained would be approximately $5748 per hectare.

Table 14: Costs associated with pest monitoring and control

	Mean	95% CI
Incurred loss $/ha	-119.95	14.11
Monitoring $/ha	10.2	0.49
Averted value $/ha	189	21.8
spraying $/ha	44.6	1.75
Coupe area (ha)	37.3	2.09

A summary of the relative frequency (RelFreq) scores for this model was obtained and the resulting matrix for the relative frequency set at 0.5, 0.75 and 0.9 are summarised in Table 15). Using the costs associated with monitoring and controlling beetle populations (For the current sampling regime, all forestry coupes are monitored, which in this case is 300, so the incurred cost of monitoring is 300x$10.2 per hectare. The number of results above 0.3 was 61 so the averted value for coupes minus the cost of spraying was 61x($189-$44.6) per hectare, and there is no incurred loss as all coupes were monitored so effectively sprayed. Therefore the predicted net

profit obtained would be approximately $5748 per hectare.

Table 14), the predicted net profit for the model with the RelFreq set at 0.5 is approximately -$938 per hectare, for RF of 0.75 the net profit is approximately $1973 per hectare and for a RF of 0.9 the net profit is $5468 per hectare. As the net gain per hectare is lower for the model in all instances when compared with monitoring all coupes using the current sampling system ($5748), this shows that the model has little immediate application for Forestry Tasmania.

Table 15: error matrix for a) RelFreq = 0.5, b) RelFreq = 0.75 and c) RelFreq = 0.9

		actual	
		above 0.3	below 0.3
predicted	above 0.3	26	24
	below 0.3	35	215

		actual	
		above 0.3	below 0.3
predicted	above 0.3	39	61
	below 0.3	22	178

		actual	
		above 0.3	below 0.3
predicted	above 0.3	55	117
	below 0.3	6	122

As an alternative application of the random forest output, generalised maps showing high risk areas and low risk areas for beetle infestations were created using *Poa* proximity and elevation. This can be used by forestry managers as a simple tool in assessing general infestation likelihood for a given area.

Chapter 5 Conclusions

The aim of this study was to determine which landscape and site variables significantly affect the distribution of Tasmanian Eucalyptus Leaf Beetles to underpin better management of *Eucalyptus* plantations. Random forest models were created in an attempt to predict *P. bimaculata* beetle distributions across Tasmania, and also to determine which of 33 environmental variables were most highly correlated with the beetle distributions to test *a priori* hypotheses. The models were developed using GIS for several combinations of climate variables and districts.

The landscape variables generated using GIS included slope, aspect, curvature, hillshade, incoming solar radiation, and wetness index, while the vegetation variables included proximity to general grasslands, *Poa* grasslands, *Acacia dealbata*, tall eucalypt forests, short eucalypt forests, non-eucalypt forests and no forests. Climate combinations assessed included: (1) mean summer maximum temperature and summer rainfall for survey years, (2) 30 year average for mean summer maximum and summer rainfall, (3) 30 year average for climate variables, (4) 30 year average for climate variables and mean summer maximum temperature and summer rainfall for survey years. The district combinations included all districts, Bass only, and all districts excluding Bass.

The findings of the *a priori* hypothesis are as follows:

Hypothesis 1: Annual summer Rainfall (a measure of plantation productivity) has a strong correlation with *P. bimaculata* populations in the district Bass, however, the majority of other variables associated with plantation productivity showed low correlations. Beetle populations decreased with rainfall to 200 mm, but gradually increased in number thereafter.

Hypothesis 2: Proximity to generalized grasslands showed little correlation with beetle populations, however, proximity to *Poa* grasslands had the highest correlation with beetles of all the variables. Beetle populations decreased in number when further than ten kilometers away from *Poa* grasslands.

Hypothesis 3: The results from this study did not support the hypothesis that climate variables were highly correlated with beetle distributions.

Hypothesis 4: There was little correlation between size of coupes or eucalypt species with beetle populations.

Hypothesis 5: Beetle populations were correlated with district and age of plantation as predicted in the hypothesis. Bass, Mersey, and Derwent had higher beetle numbers than Murchison or Huon, and Bass had greater variability between years than the combination of other districts. When Bass was excluded from the model, beetle populations increased with age of plantations, between two and eight years.

Hypothesis 6: Surrounding vegetation types showed little correlations with beetle distributions, however, this is likely because the percentage of surrounding vegetation from each class was not assessed.

Hypothesis 7: This hypothesis was confirmed as increasing elevation showed a strong correlation with increasing *P. bimaculata* numbers.

Overall, distances of less than 10 kilometres to *Poa* grasslands and increasing elevation showed the strongest positive relationships with *Paropsisterna bimaculata* populations, whilst mean annual summer rainfall and survey year were important for Bass. When Bass was excluded from the model, age was of importance.

The model that showed the least error (0.18 error) was for all districts except Bass for thirty-year climate average data and summer mean rainfall and summer mean maximum temperature. However, after a cost analysis this model was still less effective than current methods of beetle analysis without any model. As this is the case two generalised maps were created for areas showing high likelihood of beetle infestations and areas of low beetle infestation using proximity to *Poa* and elevation data only. These can be used by forestry managers to get a general understanding of the risk of beetle infestations.

Further research looking at distance to *Poa* grasslands in greater detail including

more accurate information on *Poa* under other vegetation; climate variables such as rainfall at a site level rather than interpolations; and temporal variability of sites between seasons would increase our understanding of beetle infestations. This would increase the ability of plantation management to identify beetle populations and take remedial action before damage to the coupes occurs.

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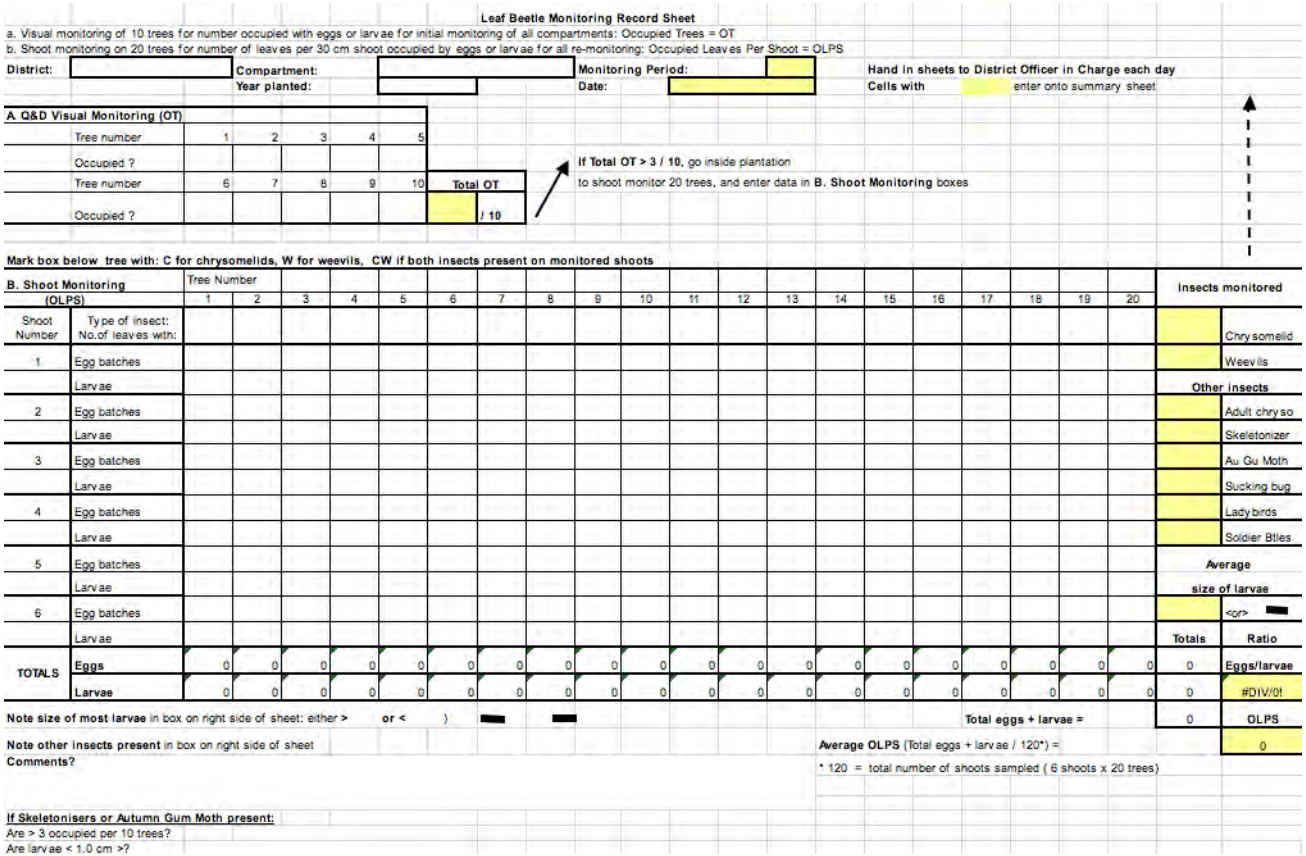
Appendix

Appendix 1: OLPS Survey sheet



Leaf Beetle Monitoring Record Sheet

a. Visual monitoring of 10 trees for number occupied with eggs or larvae for initial monitoring of all compartments: Occupied Trees = OT
b. Shoot monitoring on 20 trees for number of leaves per 30 cm shoot occupied by eggs or larvae for all re-monitoring: Occupied Leaves Per Shoot = OLPS

District: | **Compartment:** | **Year planted:** | **Monitoring Period:** | **Date:**

Hand in sheets to District Officer in Charge each day
Cells with enter onto summary sheet

A Q&D Visual Monitoring (OT)

	Tree number	1	2	3	4	5	
	Occupied ?						
	Tree number	6	7	8	9	10	**Total OT**
	Occupied ?						**/ 10**

If Total OT > 3 / 10, go inside plantation to shoot monitor 20 trees, and enter data in **B. Shoot Monitoring** boxes

Mark box below tree with: C for chrysomelids, W for weevils, CW if both insects present on monitored shoots

B. Shoot Monitoring (OLPS)		Tree Number 1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20
Shoot Number	Type of insect: No.of leaves with:																				
1	Egg batches																				
	Larvae																				
2	Egg batches																				
	Larvae																				
3	Egg batches																				
	Larvae																				
4	Egg batches																				
	Larvae																				
5	Egg batches																				
	Larvae																				
6	Egg batches																				
	Larvae																				
TOTALS	**Eggs**	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
	Larvae	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0

Insects monitored

	Chrysomelid
	Weevils
Other insects	
	Adult chryso
	Skeletonizer
	Au Gu Moth
	Sucking bug
	Ladybirds
	Soldier Bties
Average size of larvae	
	<or>
Totals	**Ratio**
0	**Eggs/larvae**
0	#DIV/0!
0	**OLPS**
	0

Note size of most larvae in box on right side of sheet: either > or <)

Note other insects present in box on right side of sheet

Comments?

Total eggs + larvae =

Average OLPS (Total eggs + larvae / 120*) =

* 120 = total number of shoots sampled (6 shoots x 20 trees)

If Skeletonisers or Autumn Gum Moth present:
Are > 3 occupied per 10 trees?
Are larvae < 1.0 cm >?

Appendix 2: DEM derivatives

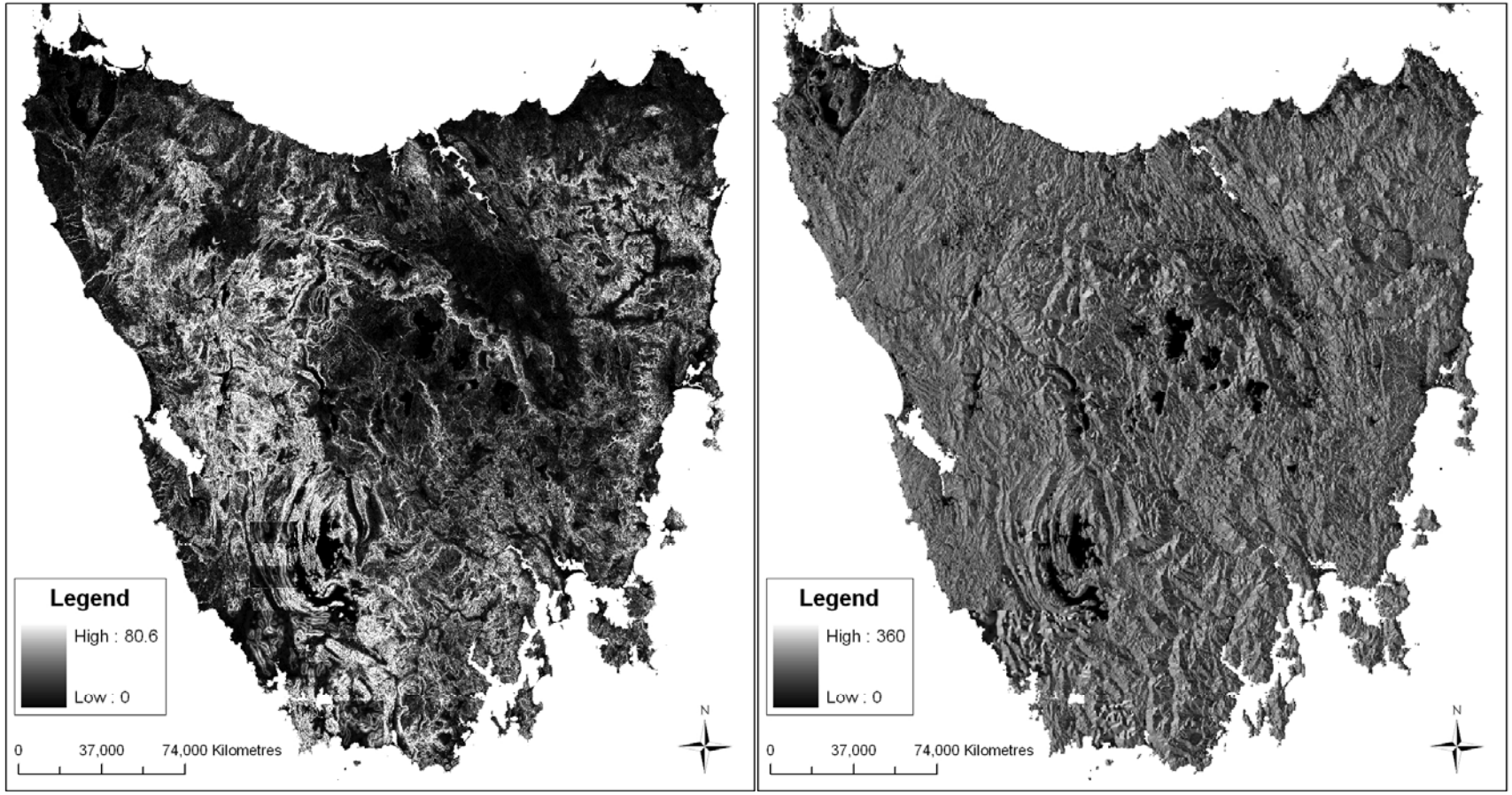


Figure 1: Distribution of slope and aspect for Tasmania

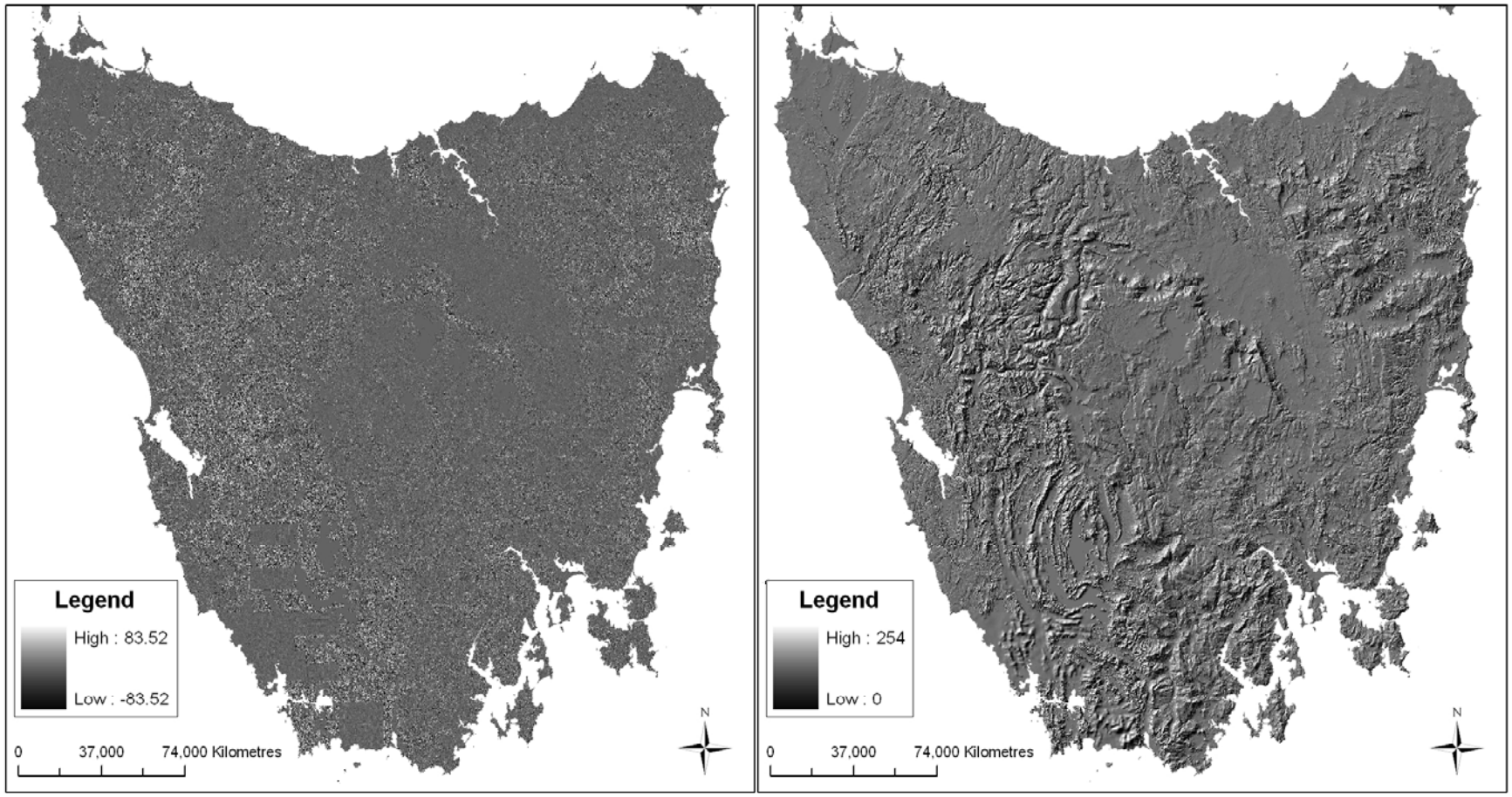


Figure 2: Distribution of curvature and hillshade for Tasmania

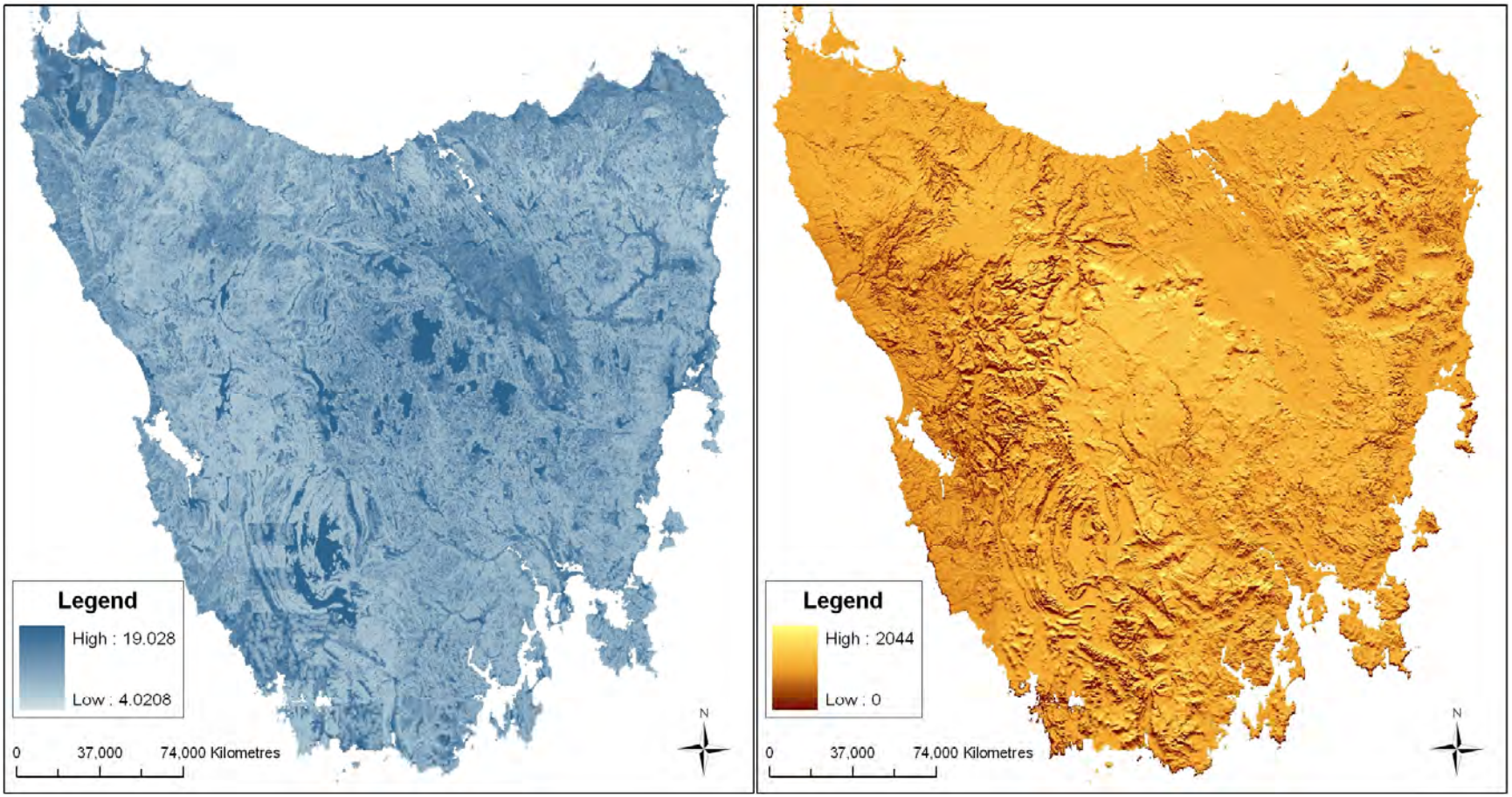


Figure 3: Distribution of wetness index and incoming solar radiation for Tasmania

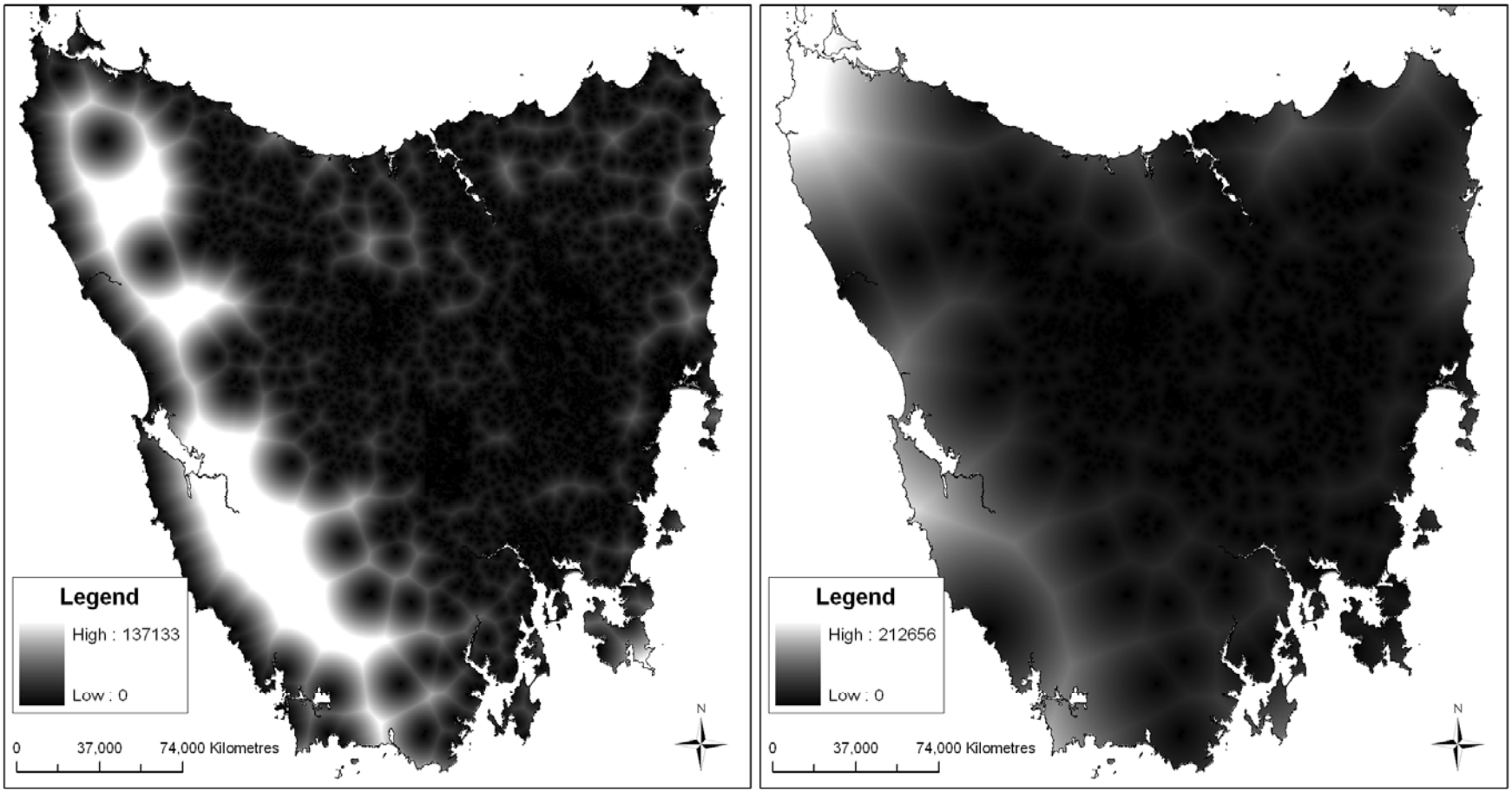


Figure 4: Proximity to general grasslands and *Poa* grassland across Tasmania

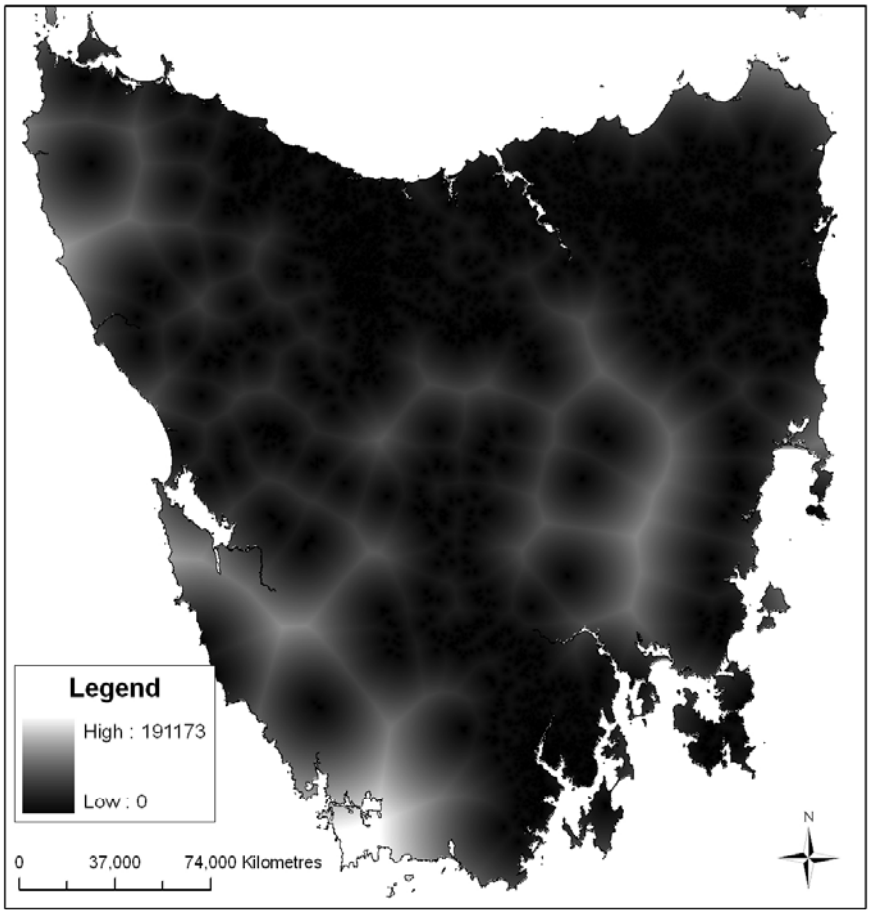


Figure 5: Proximity to *Acacia dealbata* across Tasmania

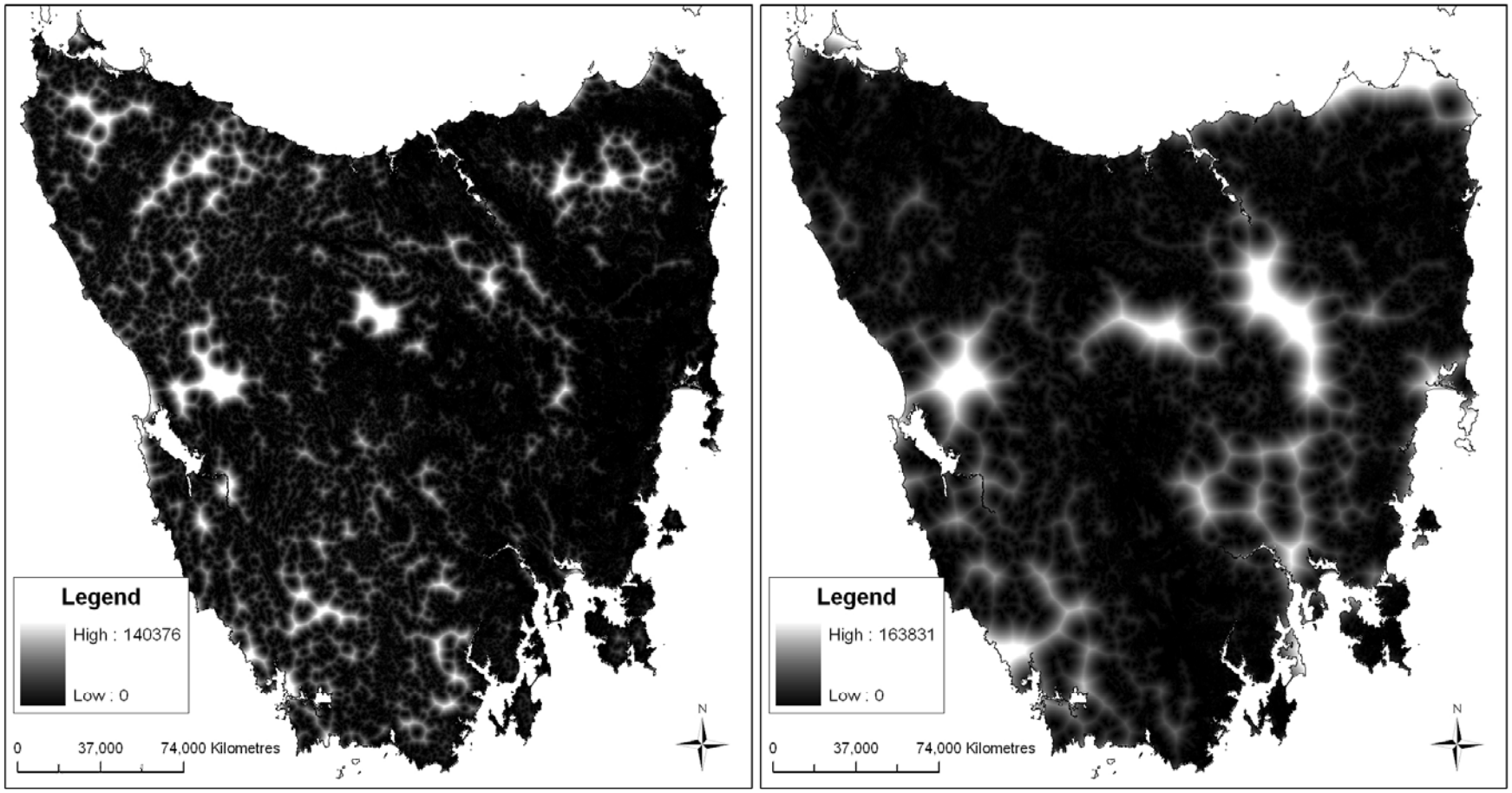


Figure 6: Proximity to eucalupt forests of low height and tall height across Tasmania

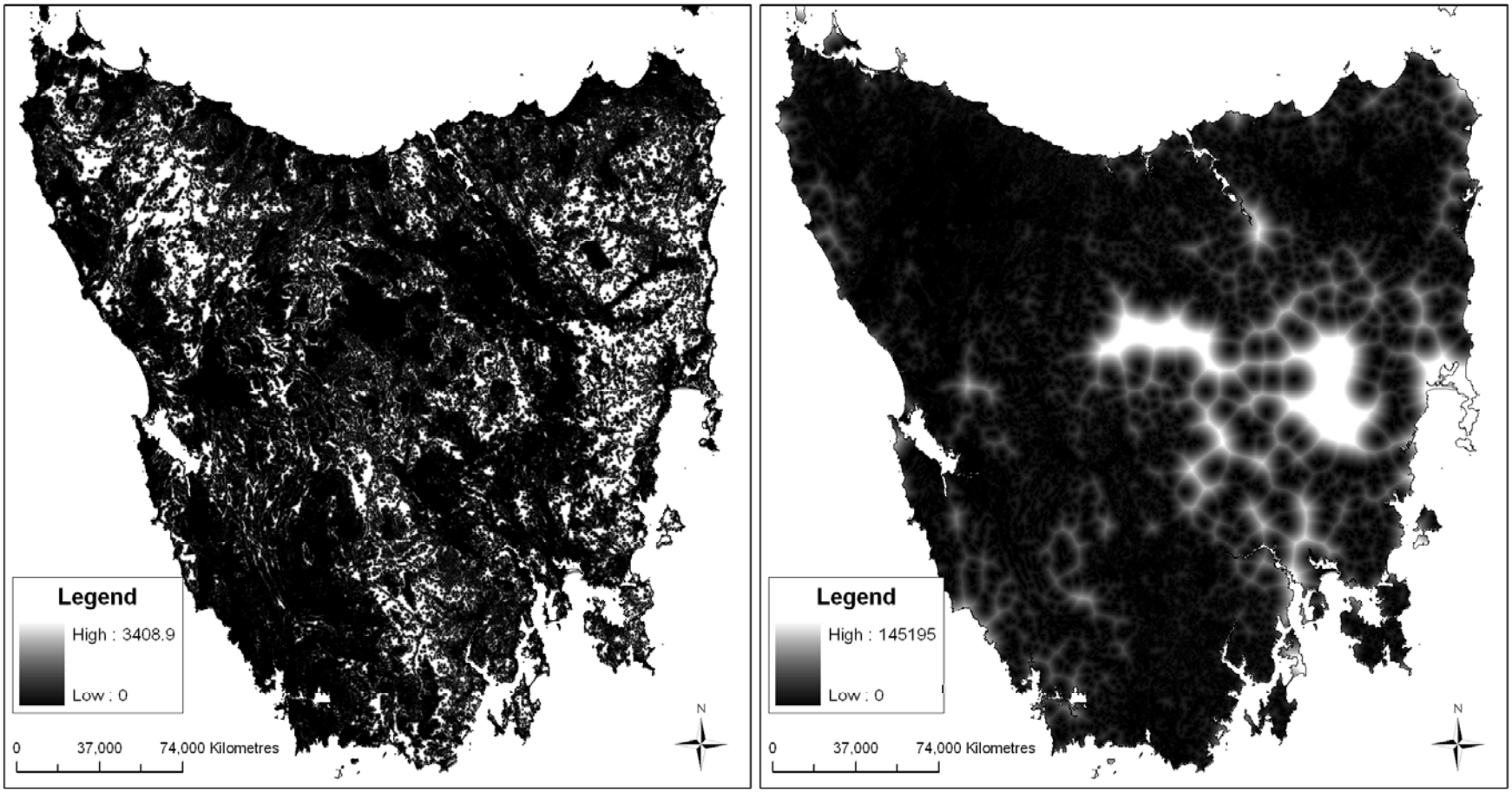


Figure 7: Proximity to areas with no forests and areas of non-eucalypt forests across Tasmania

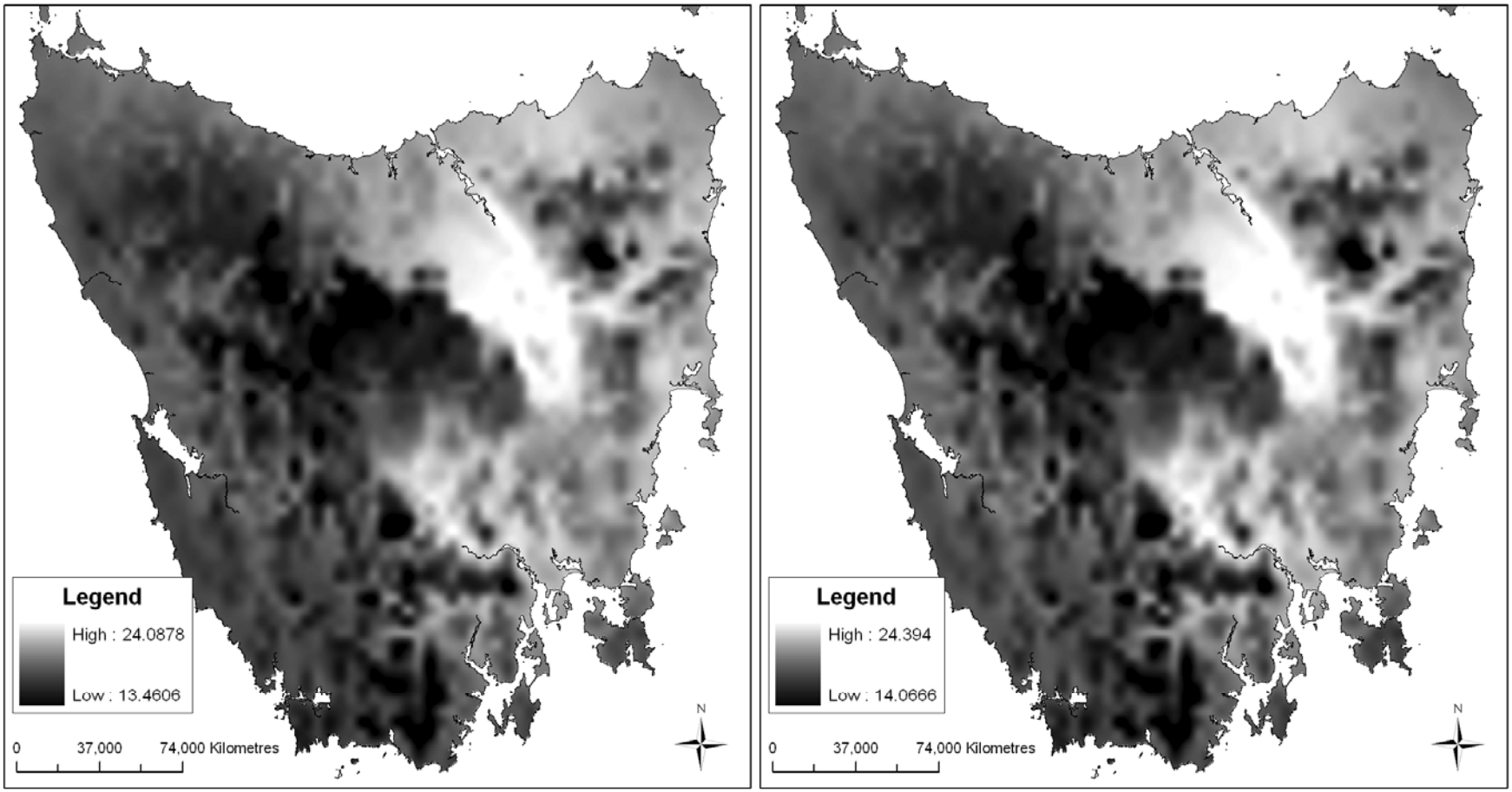


Figure 8: Distribution of mean summer temperature for 2005/2006 and 2007/2008 across Tasmania

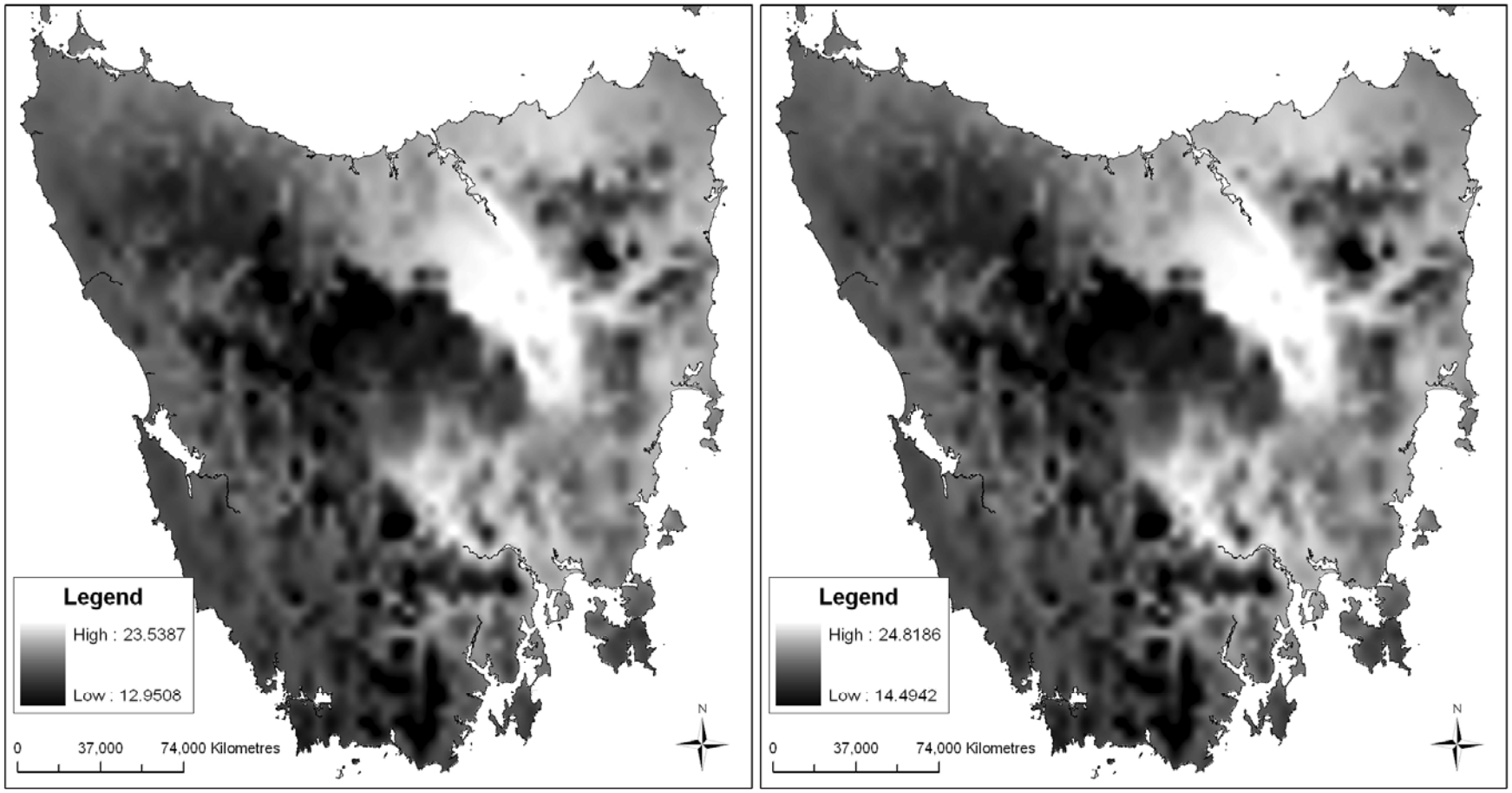


Figure 9: Distribution of mean summer temperature for 2008/2009 and 2009/2010 across Tasmania

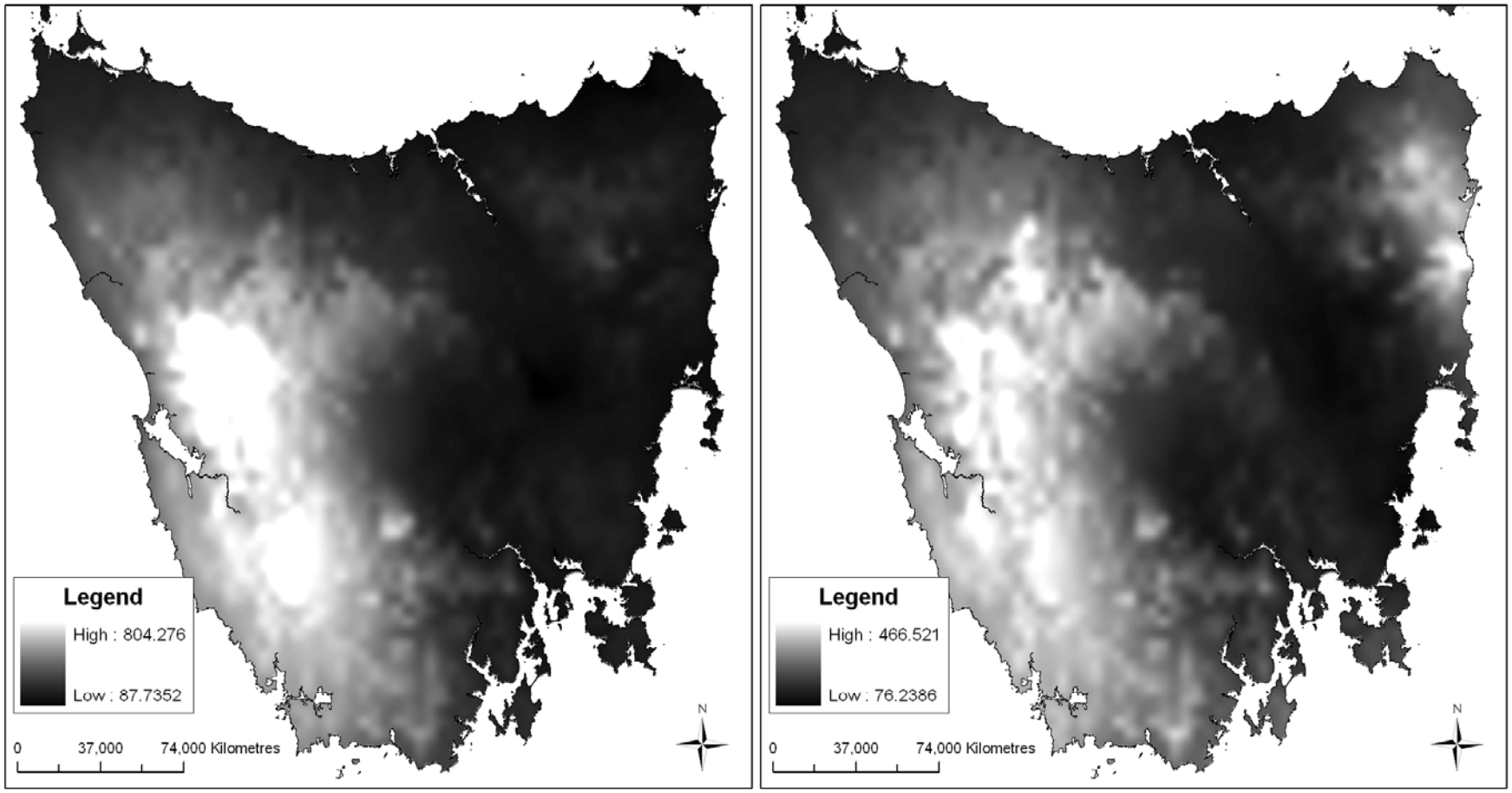


Figure 10: Distribution of summer rainfall for 2005/2006 and 2007/2008 across Tasmania

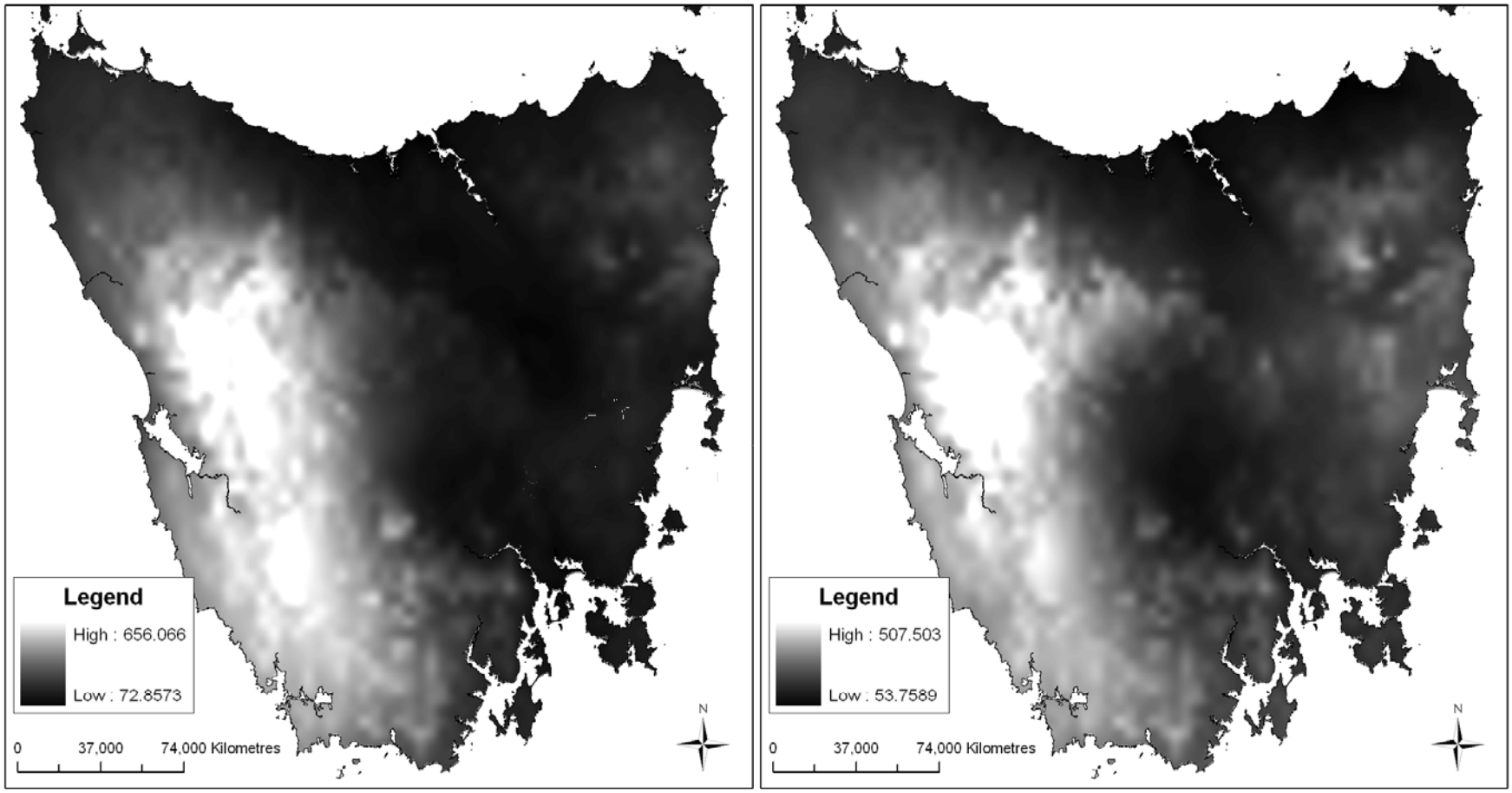


Figure 11: Distribution of summer rainfall for 2008/2009 and 2009/2010 across Tasmania

Appendix 3: Top 10 variable importance for each model tested

Table 1: Ranks of covariates as derived from variable importance plots based on models that include four different combinations of climate variables. 1) 30 year average plus actual summer rainfall and maximum temperature. 2) 30 year average for summer rainfall

1)	all years	2005/ 2006	2007/ 2008	2008/ 2009	2009/ 2010	Bass	excluding Bass	mean
Poa	1	1	2	6	1	2	2	2.14
DEM	2	3	1	5	2	5	1	2.71
Rainfall_2	4	2	3	4	5	3		4.57
survey_year	7	N/A	N/A	N/A	N/A	1		6.33
District	6	7		7	3		3	6.86
Raindays	8	4	9	1	7	9		7.00
Summer_max				2	8	4	4	7.29
Annual_evap	9	8	5	8	6		5	7.43
Summer_max_2	3	9	8	3				8.00
Annual_max	10	6	6			10	6	8.57
Ave_rad		5	10	9		6	10	8.86
rain___evap			7		9	8	7	9.14
Summer	5				4			9.14
Annual					10	7	8	9.86
For_low			4					10.00
Age							9	10.71
hillshade				10				10.86
Species		10						10.86
2)	all	2005/ 2006	2007/ 2008	2008/ 2009	2009/ 2010	Bass	Excluding Bass	mean
Poa	1	1	2	4	1	2	2	1.86
DEM	2	2	1	3	2	3	1	2.00
District	3	4	6	2	3		3	4.57
Summer	4	6	4	6	4	4	6	4.86
Summer_max	7	5	10	1	8	5	9	6.43
Grass	9	7	8	8	6	6		7.86
survey_year	5	N/A	N/A	N/A	N/A	1	7	8.14
Age	6					7	4	8.71
For_low			3		7	10		8.83
Slope	8		5	5				8.86
Acacia	10	9	9	9	9		5	8.86
Species		3				9		9.57
wetness			7		5			9.57
curvature		8				8		10.14
hillshade				7				10.43
Planted year		10					8	10.43
Area_perim					10			10.86
For_tall							10	10.86
sunlight				10				10.86

Table 1 (cont.): Ranks of covariates as derived from variable importance plots based on models that include four different combinations of climate variables. 3) actual summer temperature and rainfall in year of sampling. 4) 30 year mean for all climate variables. N/A = not assessed

3)	all years	2005/ 2006	2007/ 2008	2008/ 2009	2009/ 2010	Bass	excluding Bass	mean
Poa	1	1	2	3	1	2	1	1.57
DEM	2	2	1	4	3	4	2	2.57
Raindays	7	4	5	1	8	8	5	5.43
Annual_evap	9	10	4	9	4	3	7	6.57
District	6		9	7	2		3	7.00
Summer	4	7	8		5	6		7.43
rain___evap	10	9	3	10	7	5	9	7.57
Annual_max	5	6	6			9	6	7.71
survey_year	3	N/A	N/A	N/A	N/A	1	10	8.29
Ave_rad		3		5		7		8.43
Summer_max	8	8	10	2	9			8.43
Age							4	10.00
Species		5						10.14
Grass					6			10.29
hillshade				6				10.29
Annual					10	10	8	10.29
For_low			7					10.43
Slope				8				10.57
4)	all	2005/ 2006	2007/ 2008	2008/ 2009	2009/ 2010	Bass	Excluding Bass	mean
Poa	1	1	2	5	1	4	1	2.14
DEM	2	3	1	4	2	1	2	2.14
Rainfall_2	5	2	3	2	3	2	7	3.43
District	3	5	7	3	4		3	5.14
survey_year	6	N/A	N/A	N/A	N/A	3	5	8.29
Summer_max_	4	6	5	1	8	5		5.71
For_low			4		5	6		8.43
Age	7						4	9.43
Species		4				8		9.57
Area_perim							6	10.29
hillshade				7				10.43
sunlight			6	8				9.86
Planted year							8	10.57
Acacia	8	7		9	6	10	9	8.57
Slope	9		8	6	10			9.43
Grass	10	10	9		7	7		9.29
wetness		8	10					10.43
curvature		9			9	9		10.14
For_tall				10			10	10.71